Space Systems Cost Risk Handbook

Applying the Best Practices in Cost Risk Analysis to Space System Cost Estimates

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Preface

In 1998, Mr. Hollis Black of Boeing presented the SSCAG Risk Subgroup with the first briefing that could be considered a modern SSCAG Risk Handbook. This presentation contained the best practices accepted by the Risk Subgroup, and provided the necessary seed needed to create a Risk Handbook oriented to the entire membership.

In 2003, Mr. Raymond Covert and Mr. Timothy Anderson, while both at The Aerospace Corporation, simultaneously conceived this particular handbook. As the chairman of the Space Systems Cost Analysis Group (SSCAG) cost risk subgroup, Mr. Covert was interested in producing a document that could be used by members of the SSCAG cost risk subgroup. Meanwhile, Mr. Anderson had independently developed a risk handbook for The Aerospace Corporation and its customers. During a fortuitous meeting of the SSCAG cost risk subgroup in Los Angeles in July 2003, Mr. Covert and Mr. Anderson decided to combine efforts to expand the existing handbook into its present form and to make it available to the SSCAG membership.

This handbook is intended for anyone who is responsible for estimating the cost of space systems. The focus of the handbook is cost risk associated with space systems, but the ideas contained herein are easily transferable to non-space systems. The handbook is a compendium of best practices (as the authors see it) for conducting cost risk analyses. It is divided into five sections: The “Introduction”, “Perspectives and Applications”, “Constructing a Risk Estimate”, and “Cost Risk Examples Using Popular Cost Models”.

The Introduction section describes the topic of probabilistic cost risk analysis, provides the reader with a tutorial on cost risk analysis and provides guidance in interpreting the results. The second section, “Perspectives and Applications” provides government and commercial philosophies and applications of cost risk analysis. The third section, “Constructing a Risk Estimate” describes various tools and techniques used in creating probabilistic cost risk analyses, potential pitfalls, as well as other special topics that are often overlooked or ignored such as correlation and Monte Carlo sampling techniques. The fourth section, “Cost Risk Examples Using Popular Cost Models” shows how cost risk analysis can be performed using the Unmanned Space Vehicle Cost Model (USCM), The NASA / Air Force Cost Model (NAFCOM), PRICE, SEER, the Automated Cost Estimator (ACE) and the Aerospace Corporation Small Satellite Cost Model (SSCM). The fifth section of the handbook contains a comprehensive bibliography of seminal works in cost risk analysis.

The editors would like to acknowledge the contributions of members of the SSCAG cost risk subgroup who contributed to this handbook in ways both great and small. They include: Dr. Stephen A. Book, Melvin A. Broder, Erik Burgess, Dan Galorath, Dr. Lionel Galway, David Graham, Yvonne Lazear, Nick Lozzi, Eric Mahr, Rich Mason, Karen McRitchie, Paul Oleson, Jim Otte, Michael Pfeifer, Gregory Richardson, Dr. Mitchell Robinson, Dr. Christian Smart, Alf Smith, and Sharon Winn.

Introduction

1. Introduction

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Why We Tend to Underestimate Cost

It is extremely difficult to correctly estimate the cost of as-yet unbuilt space systems. Historically, cost estimates have consistently been too low, and acquisition officials have too often been forced to go back to Congress asking for more money. This despite the fact that most space organizations have access to highly trained, experienced, cost estimating personnel, including analysts at Air Force Space Command, NASA, Air Force Cost Analysis Agency, Naval Center for Cost Analysis and the National Reconnaissance Office.

Why has the cost community so often missed the mark on space system costs? Consider some of the players. First of all, there are the contractors. The competition for the national space budget is intense. The best way for contractors to win a source selection is to bid as low as possible, hoping to make up the difference in follow-on engineering changes.

Next are the acquisition program managers. These hard-working officials also operate in a highly competitive environment. In order to keep an acquisition program from being cancelled, program managers are often forced to behave as if nothing will go wrong with their programs. This behavior enables them to keep program office cost estimates low, but requires them to assume tremendous risks of cost growth.

Then there are the operational users. Between the time a space system is initially designed and the time it is actually deployed, threat and requirements changes force changes to the system that invariably result in higher than estimated costs.

The government budgeting process is another culprit. Since management reserve is forbidden, program managers are forced to request budgets that are less than what they think they will realistically need to cover uncertain future events.

And the cost estimators are another part of the problem. Despite the availability of cost data, cost models, and cost estimating relationships, too often cost estimators lack the necessary training to correctly apply these models. Even the independent cost agencies, who are in a position to ignore the politics of acquisition and focus only on the facts, tend to underestimate the true cost of space programs simply due to methodological issues.

There are many other reasons for this phenomenon, but one of the main reasons cost estimators underestimate acquisition costs is due to the fundamental inability to predict the future. Since it is impossible to make accurate predictions, the cost community has relied heavily on the development of cost estimating relationships (CERs), based on historical cost data, for the purpose of making statistically-based, educated guesses about the cost of systems that have yet to be built. Moreover, the use of CERs requires exact knowledge of the future system's design – even if it hasn't been designed yet! And while CERs have served the cost community well, they are fundamentally a regression curve through a subset of historical cost data, and if not used correctly, or if the wrong assumptions are made, will produce misleading results.

Figure 1-1 shows a typical CER based on historical cost data. The curve that best fits the data shown in this figure has the attractive feature of increasing as the cost driver increases. Thus, if the cost driver represents a key physical or performance parameter such as weight or power, then as weight or power increases, the cost estimate also increases. Therefore, one can use this CER by evaluating the function at any value of the cost driver, and it will provide an estimate of the cost of a similar system having that property.

Unfortunately, however, this CER also has some drawbacks. First, while the functional form tracks with the data, it doesn't correctly estimate any of them. Each data point falls some distance away from the curve. Second, some of the data points are lower than the curve, and some are substantially higher. So, had a cost estimator used this CER to estimate the cost of one of these data points, he would have missed it.

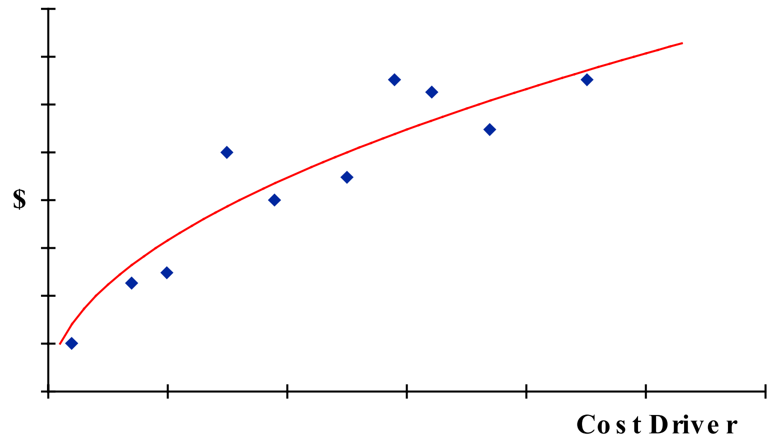


Figure 1-1 - A Typical Cost Estimating Relationship

Moreover, Mackenzie [1] has shown evidence that historical space cost data tends to be distributed such that the errors are proportional, that is, they increase as the cost driver increases, and that the errors tend to be skewed toward the high side. The implication is that gross underestimates are more likely than gross overestimates. The reason for this can be seen by studying Figure 1-2, which illustrates a typical CER's cost probability distribution.

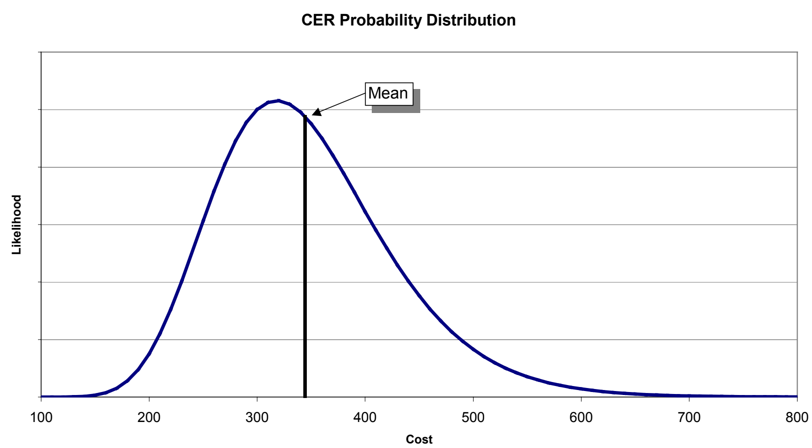


Figure 1-2 - Typical CER Probability Distribution

As this figure shows, the presence of a long right tail means there is a high likelihood that the true cost may be significantly larger that the mean. This argues for the necessity of accounting for the spread, or variability, of the data when using the CER to estimate cost.

All of this points to what is perhaps the biggest reason that we consistently underestimate the cost of space systems – the acquisition community has not fully bought in to the reality that cost estimates are *really* probability distributions and *not deterministic*. In a perfect world, cost analysts should present cost estimates as probability distributions, and acquisition decision-makers should then choose their estimate, or budget, by balancing that choice against the risk of a budget overrun. Naturally, the higher the cost, or budget, estimate, the lower the probability of a budget overrun. But the prevailing practice is that cost estimators report, say, the 50th percentile of the probability distribution as *the cost estimate*, and decision-makers choose to budget at a value that is even less than that. Consider the following exchange between a decision-maker and his cost estimator:

> ***Decision-maker:*** *So, John, how much will our future system cost?*
>
> ***Cost estimator:*** *Sir (looking at the 50th percentile number), our estimate is $52M.*
>
> ***Decision-maker:*** *Well, John, that's too high, we only have $45M in the budget to work with. We'll just have to manage to that number.*
>
> ***Cost estimator:*** *But…but...*

The implications of this practice are stunning. For one thing, since cost probability distributions tend to be "right-tailed," as Figure 1-2 illustrates, then the 50th percentile turns out to be less than the *expected* (mean) cost estimate. Additionally, if cost is estimated at the 50th percentile, this means there is a 50% chance that the true cost will be greater than the cost estimate! Moreover, when decision-makers choose to budget at a value that is even less than the 50th percentile, say the 30th percentile, then they are dooming themselves to a 70% probability of a budget overrun! This practice needs to be ended. Consider the following exchange between our decision-maker and our cost estimator *one year later*:

> ***Decision-maker:*** *John, our program is now projected to cost $60M! You told me it would be $52M! You're fired!*
>
> ***Cost estimator:*** *But…but…*

Cost estimators should explain the probabilistic nature of their estimates, and acquisition decision-makers should set budgets so that they have a reasonable probability of budgetary *success*. Here's how that initial exchange *should* have gone:

> ***Decision-maker:*** *So, John, how much will our future system cost?*
>
> ***Cost estimator:*** *Sir, we've developed the following cost probability distribution (shows the distribution to the decision-maker). This distribution has an expected value of $56M, but notice, sir, that there is a fair amount of variability in this estimate. As a matter of fact, the standard deviation of this distribution is $10M. That means the actual cost could easily exceed $66M.*
>
> ***Decision-maker:*** *Well, John, that's too high, we only have $45M in the budget to work with. We'll just have to manage to that number.*
>
> ***Cost estimator:*** *Yes, sir, I understand the budgetary constraint, but we have confidence in this cost estimate. If you really want this new system, then we need to be prepared to budget more than $45M for it. In fact, if you look at the cost probability distribution, $45M falls at the 14th percentile. That means there is only a 14% chance that $45M will be enough, with a corresponding 86% chance that the cost will exceed $45M.*

Decision-maker: *Hmmm…I see what you mean. So where should I set the budget to have, say, an 80% probability of avoiding a budget overrun?*

Cost estimator: *Well, sir, you should set the budget at the 80th percentile of the estimate or $64M.*

Decision-maker: *Okay John, thanks for the insight. I'll see what I can do about increasing the budget for this system.*

Suppose John's boss was able to reallocate the budget because of the high priority of this system. He ultimately set the budget for this system at John's recommendation of $64M. Now consider the following exchange between our decision-maker and our cost estimator one year later:

Decision-maker: *John, our program is now projected to cost $60M! But because of what you told me about budget risk, I've got enough money in the budget to cover it. Thanks again for explaining that cost probability distribution to me. I'm giving you a raise!*

Cost estimator: *Aye, aye, sir!*

The remainder of this handbook will attempt to explain and encourage the use of knowledge of variability, or uncertainty, when producing cost estimates based on CERs, how to correctly model cost estimates in a probabilistic framework, and how to explain the results to management.

What is Cost Risk Analysis?

Cost risk analysis is the set of activities necessary to (1) capture the probabilistic nature of each element of cost in a cost estimate; (2) model the probabilistic behavior of the entire cost estimate; and (3) organize and display the probabilistic nature of the cost estimate in a way that makes sense, is explainable to non-statisticians, and portrays the range of possible costs as well as their likelihoods.

Consider the example of having a house built. Suppose the major cost drivers are materials and labor. Would it be reasonable to expect a general contractor's estimate to be precise before the house is built? Of course not. There are many variables that affect the actual cost of the project. Examples include pricing variations in materials, uncertainty in the actual amount of labor and material required, unexpected damage due to weather, and other esoteric variables such as mid-stream design changes. A prudent homebuyer would assume there is some uncertainty associated with the general contractor's estimate.

A general contractor's simplistic cost estimate might go as follows:

Materials	**Qty**	**Unit Price**	**Price**
Lumber (board ft.)	3000	$ 3.25	$ 9,750.00
Concrete (cu. ft.)	2000	$ 1.50	$ 3,000.00
Drywall (sq. ft.)	8000	$ 1.50	$ 12,000.00
Windows (sq. ft.)	200	$ 10.00	$ 2,000.00
Paint (gals)	100	$ 5.00	$ 500.00
Shingles (sq. ft.)	1500	$ 4.50	$ 6,750.00
Total Materials			**$ 34,000.00**

Labor	**Man-Hours**	**Hourly rate**	**Cost**
Pour concrete	200	$ 6.25	$ 1,250.00
Build frame	2000	$ 12.50	$ 25,000.00
Install drywall	3000	$ 9.75	$ 29,250.00
Install windows	750	$ 10.00	$ 7,500.00
Paint	500	$ 7.50	$ 3,750.00
Install roof	1000	$ 12.50	$ 12,500.00
Total Labor			**$ 79,250.00**

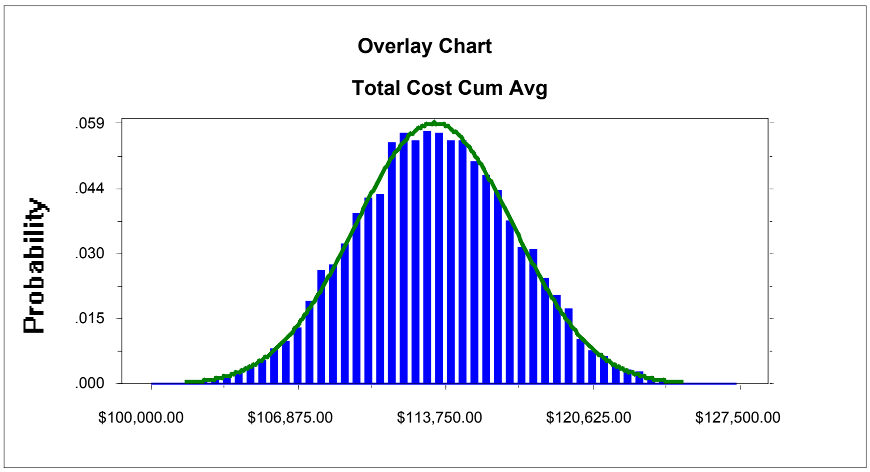
Materials	$ 34,000.00
Labor	$ 79,250.00
Total Cost	**$ 113,250.00**

Figure 1-3 - General Contractor's Estimate

But, if the prospective homeowner were to take out a mortgage for exactly $113,250, how likely is it that that amount would be enough? Since this is only an estimate, it is certainly possible that the actual total cost could be somewhat more or less than this amount.

Let's now use a cost risk analysis approach on this estimate. Suppose we allow for a plus-or-minus 10% variation in quantity and unit pricing of materials, as well as plus-or-minus 10% variation in labor man-hours and hourly rate[1]. Then the range of possible costs lies anywhere between $91,732.50 and $137,032.50. This is a range of uncertainty of $45,300, or 40% of the original estimate!

Of course, it is highly unlikely that all variables will fall at either their lower or upper limits, so a more useful interpretation of cost risk is the probability distribution of cost. As Figure 1-4 below illustrates, the actual cost is much more likely to lie somewhere close to the center of the distribution. In fact, there is a 90% chance that the true cost will lie between $107,213.00 and $119,355.00. Moreover, there is only a 5% chance that the true cost will fall below $107,213.00 and a corresponding 5% chance that the true cost will exceed $119,355.00. Indeed, armed with this information, a prudent home-buyer would be quite comfortable taking out a mortgage for, say, $119,355.00 – only $6,105.00 more than the expected cost – and be 95% confident that the mortgage will cover the actual cost!



Mean	$113,253.25
Standard Deviation	$3,707.79
Percentile	
0%	$100,734.45
10%	$108,420.29
20%	$110,067.13
30%	$111,253.92
40%	$112,253.42
50%	$113,222.33
60%	$114,215.17
70%	$115,257.89
80%	$116,434.49
90%	$118,091.47
100%	$125,617.54

Figure 1-4 - Probability Distribution of Total Cost

The preceding example shows the utility of performing a cost risk analysis on any acquisition in which costs are subject to variability. The example portrays all of the important aspects of a good cost risk analysis:

1. It captures the probabilistic nature of each cost element – plus-or-minus 10%;

[1] If the cost model estimates hours based upon a simple factor of the material quantity, this could more reasonably account for how the labor would change if the material quantity changes. Of course, the factors themselves are only estimates, and they could be modeled to vary by ± 10%. In this case, the bounds change to $105.4 to $121.5. Other relationships such as concrete quantity (the footprint of the building) to the other materials could further broaden the estimate.

2. It models the probabilistic nature of the total cost, and;
3. It organizes and displays the probabilistic nature of the cost estimate in a way that makes sense, is explainable to the prospective homebuyer, and portrays the range of possible costs as well as their likelihoods.

References

[1] Mackenzie, Donald; and Addison, Bonnie, “Space System Cost Variance and Estimating Uncertainty,” *Wyle Laboratories*, Proceedings, 2002 ISPA Annual Conference, May 2002.

[2] Anderson, T.P., “Cost Risk Tutorial,” *The Aerospace Corporation*, Space Systems Engineering Risk Management Symposium, Manhattan Beach, CA, February 2004.

2. A Tutorial on Cost Risk Analysis

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"It's not what you don't know that hurts you – it's what you DO know that isn't true."

- Dr. Stephen A. Book [1]

So, what is it that we think we know? We think we know the total cost of the system! When building a cost estimate using CERs, the naïve approach is to develop a work breakdown structure (WBS) for the system, make a best estimate of cost for each element of the WBS using CERs, then roll up each of these best estimates to obtain the best estimate of the total cost. But, as Book [1] points out, the point estimate produced using this naïve approach usually underestimates the true expected cost by a wide margin.

Definitions of Cost Risk Related Terms

In April 2002, the NRO Cost Group's Cost Risk Working Group, with assistance from Dr. Paul Garvey of MITRE and Dr. Stephen Book of MCR, defined the following cost risk related terms:

Risk is the chance of uncertainty or loss. In a situation that includes potentially favorable and unfavorable events, *risk* is the probability that an unfavorable event occurs.

Uncertainty is the indefiniteness about the outcome of a situation. *Uncertainty* includes both favorable and unfavorable events. Once the overall amount of *uncertainty* is understood, then it is possible to assess *risk*.

Cost Risk is a measure of the chance that, due to unfavorable events, the planned or budgeted cost of a project will be exceeded.

Cost Uncertainty Analysis is a process of quantifying the cost estimating uncertainty due to variance in the cost estimating models as well as variance in the technical, performance and programmatic input variables.

Cost Risk Analysis is a process of quantifying the cost impacts of the unfavorable events.

The Key to Understanding Risk and Uncertainty

A basic understanding of probability theory is the key to understanding cost risk. Cost models are not exact, but rather capture historical program cost trends. The result of a CER is most correctly interpreted as the *expected* cost of a system that has a given cost driver.

Why are CERs inexact? All programs are subject to unforeseeable events such as requirements growth, hard engineering problems, test failures, schedule slips and unknown unknowns. So, when developing CERs, the best we can do is to create a model that approximates the cost, on average, given the data used to produce the model. Statistical theory permits us to overlay a probability distribution on the result of the CER, and probability theory provides tools for discussing uncertainty in future costs arising from inexact cost models and unforeseen program challenges.

Consider a simple example – predicting the price of a loaf of bread. Mankind has been baking bread for thousands of years, so this should be easy. Assuming all local grocery stores price their bread independently, one could consider the price of a loaf of bread at each grocery store as a random variable. Table 2-1 provides a partial list of bread prices at some local stores.

Table 2-1 - Bread Prices

Safeway	$	1.38
Giant	$	1.25
Food Lion	$	1.41
Commissary	$	1.22
7/11	$	1.44
•		
•		
•		
Ralphs	$	1.24

Suppose one were to sample the prices at several local grocery stores. It would then be possible to develop a histogram, or probability distribution, of bread prices. Statistical techniques allow us to fit the histogram with a smooth probability distribution as shown in Figure 2-1.

From this probability distribution, we can determine that the price of bread, as obtained from this sample, is approximately normally distributed with a mean of $1.29 and a standard deviation of $0.20.

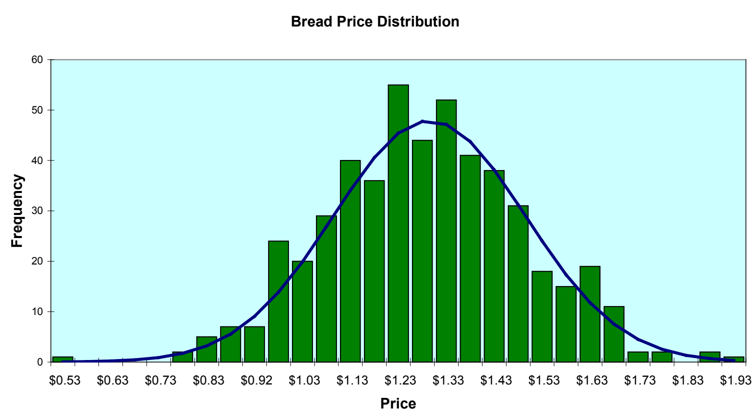

Figure 2-1 – Bread Price Distribution

This bread price probability distribution provides several pieces of useful information:

1. Most stores sell bread at a price near $1.29 per loaf;
2. Very few stores sell bread at a price near the tails of the distribution;
3. Nearly all stores sell bread at a price that falls within ± 3 standard deviations from the mean;
4. Half of the stores sell bread at a price at or below $1.29 per loaf, and the other half sell bread at a price above $1.29 per loaf.

But notice that if you were to stop at a *randomly* selected store with *exactly* $1.29 in your pocket, you would have only a 50% chance of being able to leave the store with a loaf of bread!

Compare This to Space System Cost Estimates

Space system cost estimates follow the same principles developed above. The result of the CER usually represents the expected (mean) cost, based on the value of the cost driver, for a system or subsystem, and is dependent on the data used to develop the CER. Moreover, the standard error of the CER corresponds to the standard deviation of the bread price distribution. Thus, the CER gives a mean and an associated standard deviation. So, a cost estimate resulting from a CER is *really* an estimate of a probability distribution with an expected value (mean) and a measure of variance (standard error).

This is an extremely important point. **Think of the result of a CER not as a deterministic *number*, but rather as a *probability distribution*.**

Consider the following properties of CERs:

1. CERs are statistically derived from historical cost data;
2. The result is that a space system cost estimate is REALLY an estimate of a probability distribution of cost;
3. Regardless of the NUMBER produced by the CER, the likelihood that the system or subsystem will cost exactly what is reported is virtually ZERO;
4. How much more or less the actual cost will be depends on the standard deviation of the cost probability distribution.

We will use these properties of a CER when developing the overall probability distribution of the cost of a space system.

Figure 2-2 expands on the notional CER shown in Figure 1-1. In this case we illustrate the probabilistic nature of CERs.

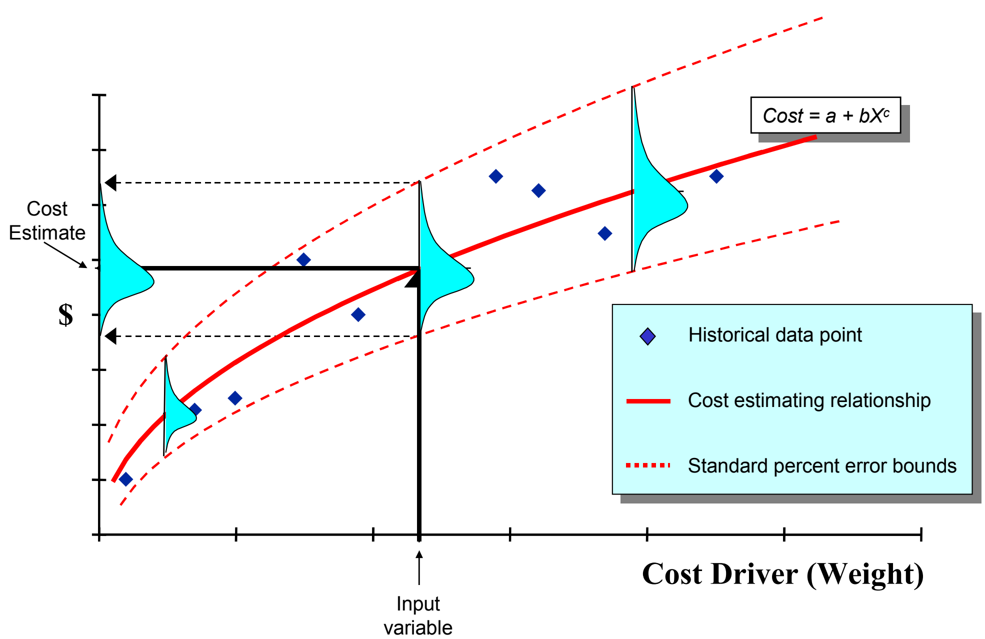

Figure 2-2 - Probabilistic nature of CERs

Under the usual modeling assumptions, the CER value for a given input variable represents the mean[2] of a probability distribution that has a standard error, or standard percent error. This particular example shows a CER with multiplicative errors. Thus, for any value of cost driver, the resulting cost estimate, projected onto the cost axis, is a probability distribution with a mean and a standard deviation.

A simple CER may be something like the following:

$$\text{Space Gadget cost} = 45 + 93(\text{weight})^{0.78}$$
$$\text{Standard Percent Error (SPE)} = 34\%$$

This means that, historically, Space Gadget costs vary according to their weight. If the weight of a future Space Gadget is, say, 100 lbs, then its expected cost would be predicted as:

$$45 + 93(100\,\text{lbs})^{0.78} = \$3,422$$

The 34% standard percent error means that for a Space Gadget with a weight of 100 lbs, the standard deviation of the cost estimate is:

$$\$3,422 \times 0.34 = \$1,163\,.$$

The uncertainty described in the previous example is known as *cost modeling uncertainty*. The cost driver, or input variable, was assumed to be deterministic. Often, however, there is disagreement or lack of absolute knowledge about the cost driver. As opposed to cost modeling uncertainty, the uncertainty associated with the cost driver is known as *cost driver uncertainty*. Both types of uncertainty should be considered in a cost estimate.

Suppose that while the weight of the Space Gadget is thought to most likely be about 100 lbs, improvements in technology might be able to reduce its weight to as low as 90 lbs. On the other hand, requirements creep could cause the weight to double in size. This cost driver uncertainty can be modeled with an asymmetric probability distribution having a long right tail as illustrated in Figure 2-3.

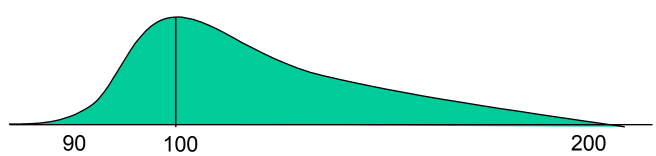

Figure 2-3 - Cost Driver Uncertainty Distribution

The implication of having an uncertain input variable is that it is now necessary to feed a probability distribution into the CER rather than a deterministic number. This naturally affects the probability distribution of the CER as shown in Figure 2-4.

[2] Not all CERs produce *means*. For example, the numerical result of log-linear CERs – those produced using ordinary least squares regression on *ln X* and *ln Y* data – actually give the *median* of the underlying cost distribution. However, in those cases, it is generally possible to adjust the CER output to the *mean* using a trivial multiplier such as the “Ping factor” [2].

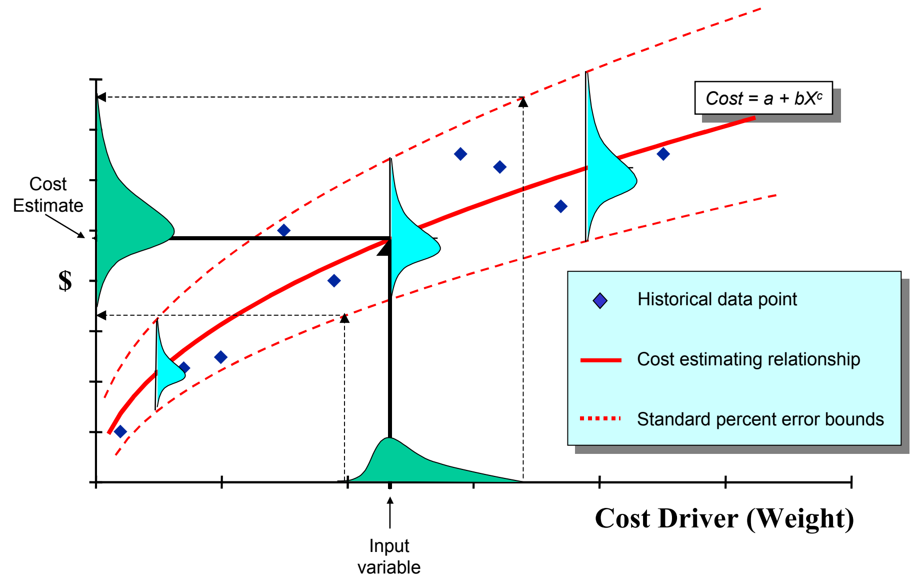

Figure 2-4 - Uncertain input variable leads to wider cost estimate distribution

The uncertainty of the input variable increases the uncertainty of the cost estimate. This is because it is possible that the input variable may be as low as its lower bound, or as high as its upper bound, or anywhere in between those two values. So, comparing Figure 2-4 to Figure 2-2, it is apparent that the resulting cost estimate probability distribution is wider when the input variable has uncertainty.

Inserting a probability distribution into a CER instead of a deterministic input variable is not a trivial exercise. It must be done correctly, via convolution or Monte Carlo simulation. Convolutions require that we add, multiply, and otherwise combine *probability distributions* rather than *numbers*. Convolving functions of distributions mathematically can be tricky and is not recommended in most cases[3]. It is much easier to do this using Monte Carlo simulation. In the Monte Carlo simulation technique, we take a random sample from the input variable distribution, insert that sample into the CER, then take a random sample from the CER distribution that has mean and standard deviation determined by the input variable. This cost is recorded as a single sample. The procedure is then repeated thousands of times after which a frequency histogram of costs is produced. The histogram then enables us to arrive at a probability distribution of cost. The result of a Monte Carlo simulation using Crystal Ball® is illustrated in Figure 2-5.

[3] Garvey [3] discusses how this can be done using Mellin transforms.

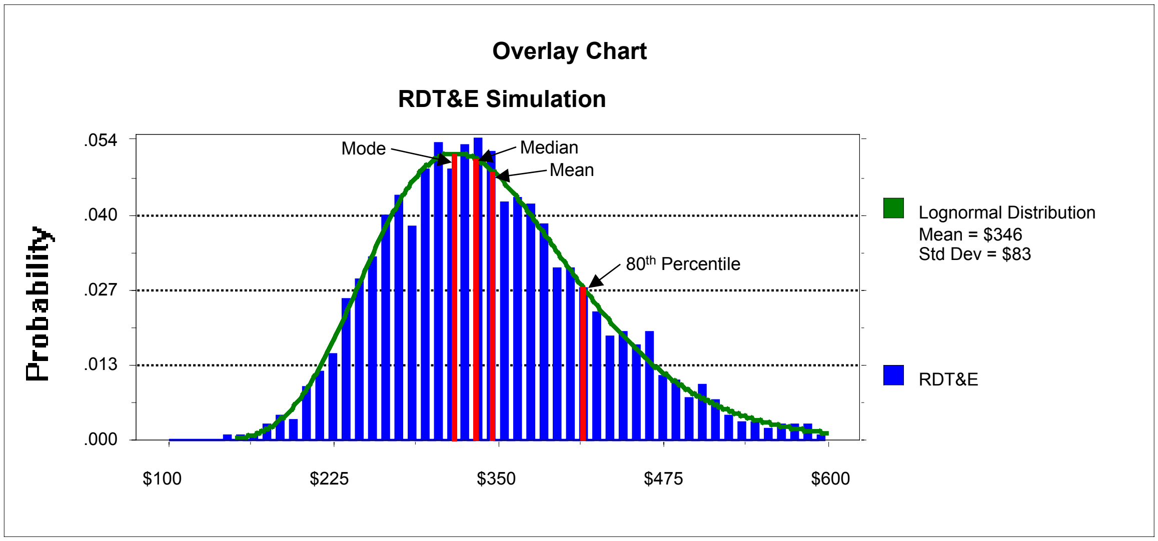

Figure 2-5 - Typical Cost Distribution

This type of result is common in cost estimates. Notice that the distribution is right-skewed, meaning that:

$$\text{Mode} \le \text{Median} \le \text{Mean}$$ [4]

Another feature of this type of distribution is that it is usually well modeled by a lognormal distribution, which has several mathematically attractive characteristics. For example, the sum of two lognormals has a lognormal distribution; the product of two lognormals is lognormal, and the ratio of two lognormals is also lognormal[5].

Rolling up Multiple WBS Elements

We've just discussed the probabilistic nature of the cost estimate of a single WBS element arrived at through the use of a CER. However, when developing space system cost estimates, we typically are required to sum several different WBS elements in order to develop a total cost estimate. In addition, sometimes we use CERs that use the result of other CERs or sums of CERs as an input variable. So, a necessary skill is to be able to probabilistically sum and/or multiply many different probability distributions with the goal of producing a total cost estimate. Figure 2-6 illustrates the procedure.

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[4] All probability distributions have at least three common measures of central tendency. The *mode* is the "most likely" value, occurring where the distribution has its maximum value; the *median* is that point where half of the probability lies to the left and the other half lies to the right; and the *mean* is the expected value or weighted average.
[5] More on the lognormal distribution is discussed in Section 2.6.4.

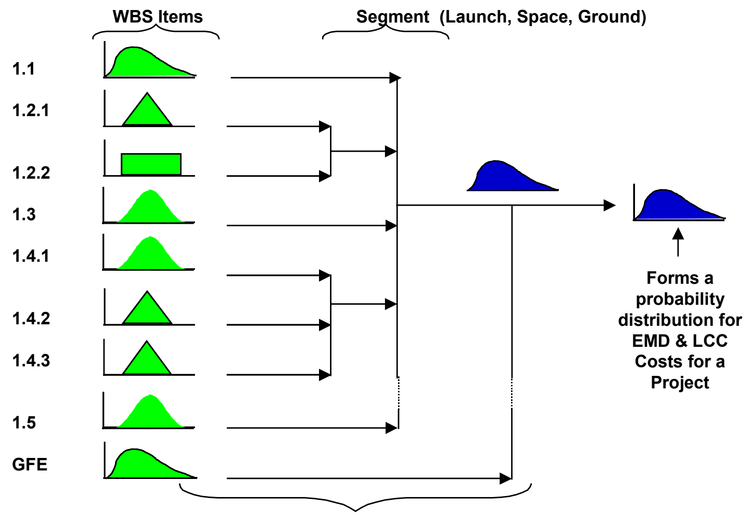

Figure 2-6 - Rollup to a Total Cost Estimate

As this figure shows, some of the WBS elements are summed, some are functions of other WBS elements, and the desired end result is a probability distribution of total cost. One of the most effective ways of accomplishing this goal is to use Monte Carlo simulation. The technique is as follows:

1. Take a random sample from each WBS element in accordance with it's probability distribution;
2. Add or multiply the result of each random sample as required to arrive at a total cost;
3. Record this total as one observation;
4. Repeat steps 1 through 3 thousands of times;
5. Develop a histogram of all total costs;
6. Use distribution-fitting techniques to convert the histogram into a total cost probability distribution.

What About Correlation?

Correlation is a very important aspect of combining cost distributions. According to Book [4] if it becomes necessary to spend more money on a particular WBS element in order to address problems, then it is probably also necessary to spend more money on other WBS elements as well. Therefore, when performing a Monte Carlo simulation, if two WBS elements are highly positively correlated then random samples should also be highly positively correlated. That is, if one sample is large, then the other should tend to be large also. In the absence of correlation, then the size of the first WBS element's sample has no effect on the size of the second WBS element's sample.

Correlation is important because it affects the variance of the total cost estimate. Suppose $X_1, X_2, \ldots, X_n$ are random variables representing the costs of WBS elements. If we are simply summing cost elements, then the total cost estimate is:

$$\text{Total Cost} = \sum_{i=1}^{n} X_i = X_1 + X_2 + \cdots + X_n \qquad (1)$$

Therefore, the mean of the total cost is:

$$\text{Mean cost} = E\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} E(X_i) = \sum_{i=1}^{n} \mu_i \tag{2}$$

and the variance of the total cost is:

$$\text{Variance of Cost} = Var\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} \sigma_i^2 + 2\sum_{j=2}^{n}\sum_{i=1}^{j-1} \rho_{ij}\sigma_i\sigma_j \ . \tag{3}$$

When the correlation term, ρ_{ij}, is zero, meaning WBS elements are independent (uncorrelated), then the variance equation reduces to:

$$\text{Variance of Cost} = Var\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} \sigma_i^2 \ . \tag{4}$$

Notice in equation (3) that, since σ is always positive, then positive correlations (i.e., $0 < \rho < 1$) increase the total variance, and negative correlations (i.e., $-1 < \rho < 0$) reduce the total variance. But, most importantly, ignoring correlation is equivalent to setting all ρ_{ij} equal to zero. Experience has shown that in cost estimation correlations tend to be positive more often than negative. Therefore, properly accounting for correlation will typically widen the total cost distribution, and ignoring correlation will lead to total cost distributions that are narrower than they should be. In any case, your estimate and range will be closer to the truth if you use reasonable non-zero correlations, than if you ignore them.

Monte Carlo simulation software, such as Crystal Ball® and @RISK®, enable the user to directly simulate statistical correlations between WBS elements. ACE RISK uses a group strength method, discussed in Section 18, to allow for statistical correlation. But how do you decide which values to use for the correlations? Covert [5] has shown that it is possible to derive the empirical residual correlation coefficients of a cost model such as the Unmanned Space Vehicle Cost Model (USCM-7) or the Small Satellite Cost Model (SSCM 2000). However, this method requires the exclusive use of either of those two cost models in order to be effective. An alternative method is to subjectively develop approximate correlation coefficients between WBS elements. This can be as simple as determining whether two WBS element are correlated by a small amount, or by a large amount, and whether that correlation is positive or negative. An example of this method is shown in Table 2-2.

Table 2-2 - Subjective Correlation Coefficients

Subjective Correlation Coefficients		
	Positive correlation	**Negative correlation**
Uncorrelated	0	0
Small amount of correlation	0.3	-0.3
Large amount of correlation	0.75	-0.75

For example, if you believe two WBS elements have a small amount of positive correlation, then you would choose a correlation value of 0.3. It is then necessary to follow documented procedures within the Monte Carlo simulation software to produce the desired correlations in your cost estimate.

Probability Distributions Useful in Cost Analysis

There are a large variety of probability distributions available for use in cost analysis. Some of the more commonly used distributions include the following:

Normal distribution

The normal distribution is defined by the following probability density function (PDF):

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left[(x-\mu)^2/\sigma^2\right]} \tag{5}$$

where -∞ < x < ∞, $\sigma > 0$, and μ is unrestricted.

Equation (5) is also known as the *Gaussian* distribution. The normal PDF is uniquely defined by the parameters μ and σ. A graph of the normal PDF is given in Figure 2-7.

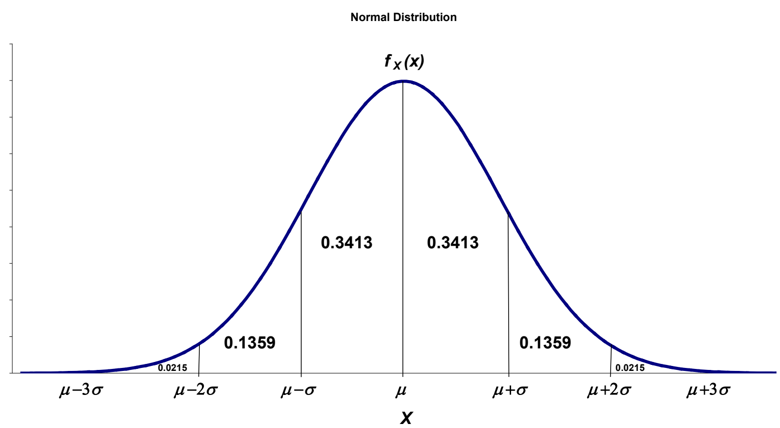

Figure 2-7 - The Normal PDF

As with any probability distribution, the area underneath the curve, $f_X(x)$, is defined as 1.0:

$$P(-\infty < X < \infty) = \int_{-\infty}^{\infty} f_X(x)dx = 1.0 \tag{6}$$

The normal distribution is symmetric about its mean μ. It also has the property that its median and mode are equal to the mean. The numbers in Figure 2-7 are the areas under the curve within the indicated intervals. In particular:

$$P(\mu - \sigma \le X \le \mu + \sigma) = \int_{\mu-\sigma}^{\mu+\sigma} f_X(x)dx = 0.6826\,. \tag{7}$$

Similarly,

$$P(\mu - 2\sigma \le X \le \mu + 2\sigma) = \int_{\mu-2\sigma}^{\mu+2\sigma} f_X(x)dx = 0.9544 \tag{8}$$

$$P(\mu - 3\sigma \le X \le \mu + 3\sigma) = \int_{\mu-3\sigma}^{\mu+3\sigma} f_X(x)dx = 0.9973 \qquad (9)$$

The remaining probability can be found under the curve beyond $\pm 3\sigma$ as the tails of the normal distribution extend to $\pm\infty$.

One might model a random variable with a normal distribution having mean μ and standard deviation σ if one expected the distribution to be symmetric, bell-shaped, and if it were conceivable that most observations would fall between $\pm 3\sigma$.

The cumulative distribution function (CDF) of the normal distribution is often of interest, since it enables calculation of the percentiles of the distribution. The CDF of the normal distribution is defined as follows:

$$F_X(x) = P(X \le x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left[\frac{(t-\mu)^2}{\sigma^2}\right]} dt\ . \qquad (10)$$

A graphical depiction of the normal CDF is shown in Figure 2-8.

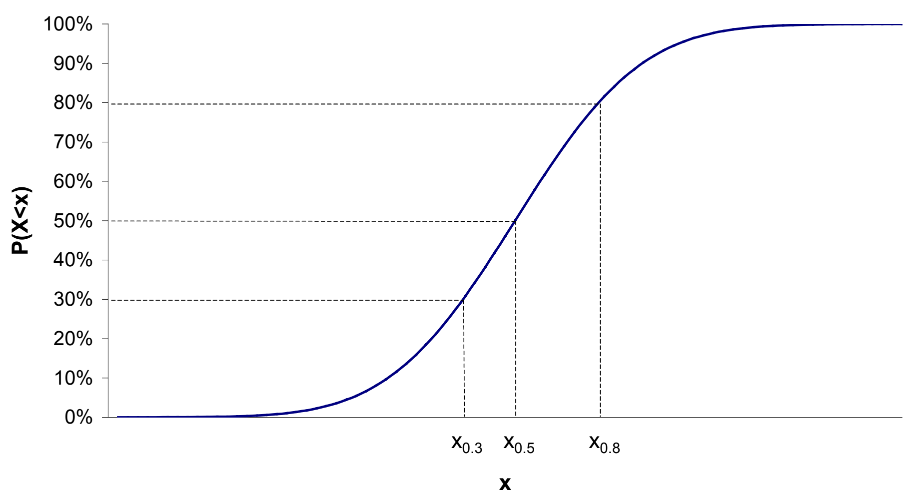

Figure 2-8 - Normal CDF

Unfortunately, the CDF of the normal distribution does not have a closed-form solution, so it is necessary to refer to standardized tables to calculate the value of $P(X \le x)$. This is performed in the following way. In order to evaluate the normal CDF, it is first necessary to standardize the random variable X. The standard normal random variable Z is defined as:

$$Z = \frac{X - \mu}{\sigma} \qquad (11)$$

Therefore, to calculate $P(X \le x)$ we evaluate

$$F_X(x) = P(X \le x) = P\left(\frac{X-\mu}{\sigma} \le \frac{x-\mu}{\sigma}\right) = P\left(Z \le \frac{x-\mu}{\sigma}\right) = \Phi\left(\frac{x-\mu}{\sigma}\right) \qquad (12)$$

where $\Phi(\bullet)$ can be found in any standard normal table. Similarly, to calculate a percentile, x_p, we look up z_p such that $\Phi(z_p) = p$, again from any standard normal table, then solve for x_p as follows:

$$x_p = \mu + z_p \sigma \tag{13}$$

Triangular distribution

The triangular distribution is commonly used as an input distribution because of its simplicity. It is easy to describe and it appeals to non-probabilists. The distribution is uniquely defined by three parameters:

1. The lowest possible occurrence (*L*);
2. The most likely occurrence (*M*);
3. And the highest possible occurrence (*H*).

Figure 2-9 illustrates the PDF of the triangular distribution.

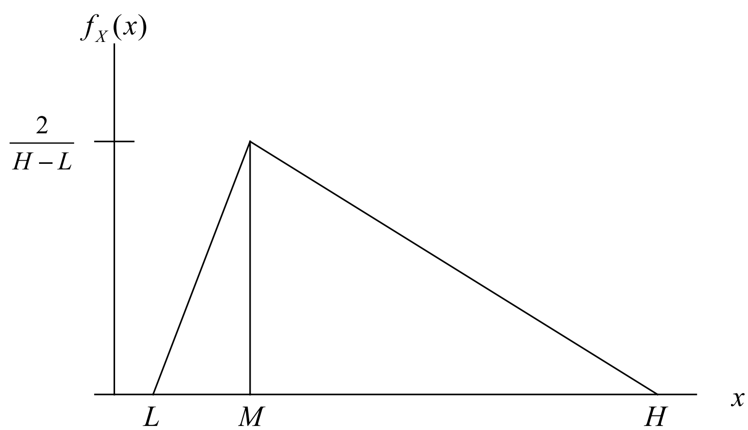

Figure 2-9 - Triangular Distribution PDF

The PDF of the triangular distribution is:

$$f_X(x) = \begin{cases} \dfrac{2(x-L)}{(H-L)(M-L)} & \text{if L} \le \text{x<M} \\ \dfrac{2(H-x)}{(H-L)(H-M)} & \text{if } M \le x \le H \end{cases} \tag{14}$$

where $-\infty < L < M < H < \infty$.

If *X* is a triangular random variable, then its mean, or expected value, *E(X)*, is:

$$E(X) = \frac{(L+M+H)}{3} \tag{15}$$

and its variance, *Var(X),* is:

$$Var(X) = \frac{1}{18}\left((M-L)(M-H)+(H-L)^2\right). \tag{16}$$

One might model the input variable distribution with a triangular distribution if all that is known is the minimum, most likely, and maximum possible values of the variable.

Uniform distribution

In some cases, all that is known is the possible range of values that the input variable might assume. In this case the uniform distribution is useful. The uniform distribution is defined by two parameters:

1. The minimum possible value (*L*);
2. The maximum possible value (*H*).

It is assumed that all observations that fall between *L* and *H* are equally likely. Figure 2-10 gives a graphical depiction of the uniform distribution.

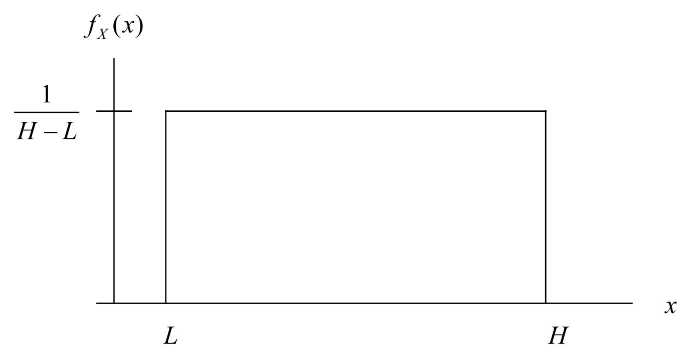

Figure 2-10 - Uniform PDF

The PDF of the uniform distribution is:

$$f_X(x) = \frac{1}{H-L} \quad \text{if } L \le x \le H \tag{17}$$

where $-\infty < L < H < \infty$.

If *X* is a uniform random variable, then its mean, or expected value, *E(X)*, is:

$$E(X) = \frac{(L+H)}{2} \tag{18}$$

and its variance, *Var(X),* is:

$$Var(X) = \frac{1}{12}\left(H-L\right)^2 . \tag{19}$$

One might model the input variable distribution with a uniform distribution if all that is known is the minimum and maximum possible values of the variable, and it is reasonable to assume that all outcomes between the minimum and maximum are equally likely.

Lognormal distribution

The lognormal distribution shows up most commonly as the error distribution for a log-linear, multiplicative error CER, or as the model for a roll-up of cost estimates after a Monte Carlo simulation. The lognormal error distribution of a multiplicative error CER falls out naturally as a consequence of using the method of log ordinary least squares (log OLS) to develop the CER. However, for roll-ups of cost estimates, the lognormal distribution is often used to model the resulting probability distribution simply because it tends to provide a good fit. This is because the histogram resulting from a Monte Carlo simulation tends to have a long right tail. A typically lognormal shaped cost distribution was shown in Figure 2-5.

The lognormal distribution is closely related to the normal distribution. If X is a non-negative random variable, and the natural logarithm of X follows a normal distribution, then X is said to have a lognormal distribution. By way of illustration, suppose $Y = ln(X)$ has a normal distribution. Then X has a lognormal distribution. This is shown graphically in Figure 2-11.

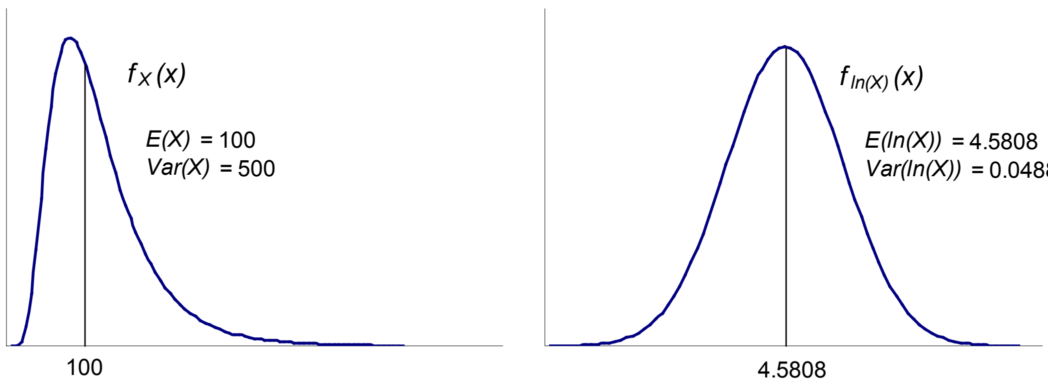

Figure 2-11 - PDFs of X and $Y = ln(X)$

The PDF of a lognormally distributed random variable X is:

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma_Y x} e^{-\frac{1}{2}\left[\frac{(\ln(x)-\mu_Y)^2}{\sigma_Y^2}\right]} \tag{20}$$

where $0 < x < \infty$, $\sigma_Y > 0$, $\mu_Y = E(ln\ X)$, and $\sigma_Y^2 = Var(ln\ X)$.

It is important to point out that μ_Y and σ_Y^2 are the mean and variance of the normally distributed random variable $Y = ln\ X$. The mean of X, $E(X)$, is:

$$E(X) = \mu_X = e^{\mu_Y + \frac{1}{2}\sigma_Y^2} \tag{21}$$

and the variance of X, $Var(X)$, is:

$$Var(X) = \sigma_X^2 = e^{2\mu_Y + \sigma_Y^2}\left(e^{\sigma_Y^2} - 1\right). \tag{22}$$

Other important statistics associated with the lognormal distribution are the mode and median:

$$Mode(X) = e^{\mu_Y - \sigma_Y^2} \tag{23}$$

$$Median(X) = e^{\mu_Y} \; . \tag{24}$$

When using the lognormal distribution to model cost, we typically do not have values of μ_Y and σ_Y^2, so a means of determining these values is necessary in order to specify the distribution function of a lognormal random variable when only *E(X)* and *Var(X)* is known. Equations (25) and (26), below, provide translation formulas for determining μ_Y and σ_Y^2 when *E(X)* and *Var(X)* are known:

$$\mu_Y = E(\ln X) = \tfrac{1}{2}\ln\left[\frac{(\mu_X)^4}{(\mu_X)^2 + \sigma_X^2}\right] \tag{25}$$

$$\sigma_Y^2 = Var(\ln X) = \ln\left[\frac{(\mu_X)^2 + \sigma_X^2}{(\mu_X)^2}\right]. \tag{26}$$

So, using equations (25) and (26), one can derive the parameters μ_Y and σ_Y^2 that uniquely specify the lognormal PDF.

Like the normal distribution, the cumulative distribution function (CDF) of the lognormal distribution is often of interest, since it enables calculation of the percentiles of the distribution. The CDF of the lognormal distribution is defined as follows:

$$F_X(x) = P(X \le x) = \int_0^x \frac{1}{\sqrt{2\pi}\sigma_Y t} e^{-\frac{1}{2}\left[\frac{(\ln t - \mu_Y)^2}{\sigma_Y^2}\right]} dt \; . \tag{27}$$

A graphical depiction of the lognormal CDF is shown in Figure 2-12.

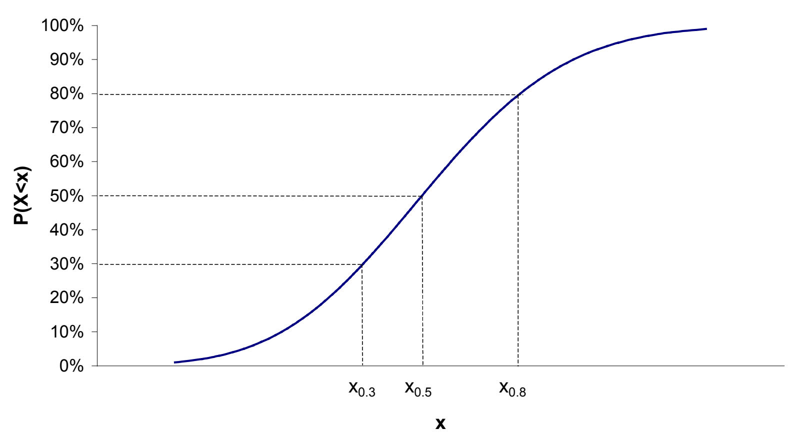

Figure 2-12 - Lognormal CDF

As in the case of the normal distribution, the CDF of the lognormal distribution does not have a closed-form solution, so it is again necessary to refer to standardized tables to calculate the value of $P(X \le x)$. This is performed in the following way. In order to evaluate the lognormal CDF, it is first necessary to standardize the random variable *X*. Because *Y* = ln(*X*) has a normal distribution, a lognormal random variable *X* can be standardized as follows:

$$Z = \frac{Y - \mu_Y}{\sigma_Y} = \frac{\ln X - \mu_Y}{\sigma_Y} \tag{28}$$

Therefore, to calculate $P(X \le x)$ we evaluate

$$F_X(x) = P(X \le x) = P\left(\ln X \le \ln x\right) = P\left(\frac{\ln X - \mu_Y}{\sigma_Y} \le \frac{\ln x - \mu_Y}{\sigma_Y}\right)$$

$$= P\left(Z \le \frac{\ln x - \mu_Y}{\sigma_Y}\right) = \Phi\left(\frac{\ln x - \mu_Y}{\sigma_Y}\right) \tag{29}$$

where $\Phi(\bullet)$ can be found in any standard normal table. Similarly, to calculate a percentile, x_p, we look up z_p such that $\Phi(z_p) = p$, again from any standard normal table, then solve for x_p as follows:

$$\ln x_p = \mu_Y + z_p \sigma_Y \quad \Leftrightarrow \quad x_p = e^{\mu_Y + z_p \sigma_Y} \tag{30}$$

This and other useful probability distributions can be found in Garvey [3] and other probability and statistics texts.

Guidelines for Choosing Probability Distributions

In order to statistically combine WBS element cost estimates into a total cost estimate, it is necessary to choose the type of probability distribution that most realistically models both input distributions and CER output distributions. Some general guidelines are suggested for making these choices.

CER Output Distributions

These are the distributions that typically fall out as a result of the method used to develop the CERs. The two most common choices are normal and lognormal.

1. **Normal**. The *normal* distribution is *assumed* when the CER is the result of ordinary least squares (OLS), or when the CER was developed using general error regression methods (GERM) and the errors were assumed to be additive. The numerical result of the CER represents the mean of the distribution, and the standard deviation is defined by the standard error of the CER. The normal distribution may also be assumed when the distribution of the sum, or some other combination, of several CERs, produced using Monte Carlo simulation, results in a Gaussian histogram (i.e., one in which the mean, median, and mode are all approximately equal, and bell-shaped).

2. **Lognormal**. The *lognormal* distribution is *assumed* when the CER is developed using log OLS, or when the CER was developed using GERM, and the errors were assumed to be multiplicative or proportional. For log OLS CERs, the numerical result of the CER corresponds to the *median* of the probability distribution, and the numerical result must be adjusted to the mean through the use of a multiplier commonly known as the "Ping" factor[6]. To a good degree of approximation, a factor can be calculated from equation (21) as follows. Suppose such a CER is evaluated with result $\tilde{\mu}$. Suppose further that the log standard error is *LSE*. Then the approximate adjustment factor is:

[6] The Ping Factor is a solution, popularized by Dr. Shu-Ping Hu for adjusting the median to the mean of log OLS CERs. [Ref. 2]

$$\mathrm{k} \approx e^{\frac{1}{2}\left(\frac{n-m}{n}\right)LSE^2} \tag{31}$$

where n is the number of data points and m is the number of coefficients estimated.

And the mean of the CER in unit space can then be derived as:

$$\mu \approx \widetilde{\mu} \cdot e^{\frac{1}{2}\left(\frac{n-m}{n}\right)LSE^2} \tag{32}$$

The standard deviation of the log OLS CER is also a function of *LSE*. Using equation (22), the standard deviation can be determined as follows:

$$\sigma \approx \sqrt{2\widetilde{\mu} \cdot e^{\left(\frac{n-m}{n}\right)LSE^2}\left(e^{\left(\frac{n-m}{n}\right)LSE^2} - 1\right)} \tag{33}$$

Approximations, rather than equalities, are shown in equations (31) through (33) since these equations require that *m* and *LSE* be *known* rather than *estimated* through regression.

In the case of CERs developed using GERM with multiplicative errors, the numerical result of the CER corresponds to the *mean* of the probability distribution, and the standard deviation of the CER is defined by the standard percent error of the regression.

CER Input Distributions

These are the distributions we desire to insert into our CERs in order to model technical uncertainty (e.g., the distribution of the input variable in Figure 2-4). Typical choices are:

1. **Deterministic**. One choice is to have no distribution at all. If a deterministic input is used, then only cost modeling uncertainty will be reflected in the result of the CER. For example: structure weight is equal to 120 lbs.
2. **Uniform**. Use this distribution if a range of values, bounded by a low and high value, with all values in between equally likely to occur, best represents the input variable. For example, structure weight may be anywhere between 100 and 130 lbs, with any value in between equally likely to occur.
3. **Triangular**. The triangular distribution can be used if you believe there is a "most likely" value around which "most" of the probability occurs, but the variable is still best represented by a range of values, bounded by an absolute low and absolute high value. For example, structure weight is most likely to come in at about 120 lbs, but may be as low as 100 lbs, or as high as 200 lbs.
4. **Normal**. The normal distribution may be necessary if the CER is a function of another CER's output. For example, the CER for spacecraft bus systems engineering, integration and test, and program management (SEITPM) might be a function of the total bus recurring hardware estimate. The normal distribution will usually be appropriate if the CER that supplies the input is a CER with additive errors.
5. **Lognormal**. Like the normal distribution, the lognormal distribution may be necessary if the CER is a function of another CER's output, particularly in the case in which the CER that supplies the input is a CER with multiplicative errors.
6. **Others**. There exist a plethora of other distributional shapes one may choose from to model the technical uncertainty of an input variable. For example, the OSD CAIG prefers the Weibull distribution over the triangular distribution because the Weibull allows for very long tails while

keeping the bulk of the probability in a specific range. Information about other input distributions can be found in various probability and statistics literature.

References

[1] Book, Stephen A., "Fictions We Live By," *The Aerospace Corporation*, Society of Cost Estimating and Analysis, September 1995.

[2] Hu, Shu Ping, and Sjovold, A.R., "Error Corrections for Unbiased Log-Linear Least Square Estimates," *Tecolote Research, Inc.*, October 1987.

[3] Garvey, Paul R., *Probability Methods for Cost Uncertainty Analysis: A Systems Engineering Perspective*, Marcel-Dekker, Inc., 2000.

[4] Book, Stephen A., "Why Correlation Matters in Cost Estimating," *The Aerospace Corporation*, 32nd Annual DoD Cost Analysis Symposium, February 1999.

[5] Covert, Raymond P., "Comparison of Spacecraft Cost Model Correlation Coefficients," *The Aerospace Corporation*, SCEA National Conference, June 2002.

[6] Anderson, T.P., "Cost Risk Tutorial," *The Aerospace Corporation*, Space Systems Engineering Risk Management Symposium, Manhattan Beach, CA, February 2004.

3. Example Cost Estimate

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The following example of a cost estimate is derived from the FireSat Cost Estimate in [1]. The FireSat is a fictional satellite program that is designed to fly in a low earth orbit (LEO). Its payload consists of an electro-optical sensor that detects forest fires in North America. This example is a cost estimate of the FireSat's Ground Segment effort. CERs are from the Unmanned Space Vehicle Cost Model version 7 (USCM-7) and other parametric techniques described in [1]. Costs are expressed in FY00$M.

It is assumed that the reader understands how cost estimates are constructed. The focus of this section will be on quantifying the uncertainty associated with the cost estimate.

Deterministic Roll-Up Method

First, we will develop the FireSat Ground Segment cost estimate using the deterministic roll-up procedure. In this procedure, cost and technical uncertainty will be ignored.

Work Breakdown Structure (WBS)

The WBS for the FireSat Ground Segment is given below:

Ground Segment and Operations (FY00$K)

Ground Segment Software (SW)
Facilities (FAC)
Equipment (EQ)
Logistics
Systems Level
  Management
  Systems Engineering
  Product Assurance
  Integration and Test

Total Ground Segment and Operations

CER Input Variables

For the FireSat Ground Segment estimate, there is only one input variable. The Ground Segment software cost is estimated from a CER using software lines of code (SLOC) as the input variable. As will be shown in a moment, the remaining WBS elements are functions of the Ground Segment Software cost estimate. Below is the input variable, such as that proposed by the contractor or program manager, typically found in the cost analysis requirements description (CARD) if one exists, or in other data sources.

- Ground Segment Software – 100KSLOC

Cost Estimating Relationships

The CERs used in the Ground Segment cost estimate are listed below. Since the reference material gives no information on the standard errors of the CERs, each is assumed to have a 25% standard percent estimating error for purposes of illustration.

- Ground Segment Software:
  - FY00$K = 220 x KSLOC
  - SE = 25% (assumed)
- Facilities:
  - FY00$K = 18% x (Ground Segment Software)
  - SE = 25% (assumed)
- Equipment:
  - FY00$K = 81% x (Ground Segment Software)
  - SE = 25% (assumed)
- Logistics:
  - FY00$K = 15% x (Ground Segment Software)
  - SE = 25% (assumed)
- Program Management:
  - FY00$K = 18% x (Ground Segment Software)
  - SE = 25% (assumed)
- Systems Engineering:
  - FY00$K = 30% x (Ground Segment Software)
  - SE = 25% (assumed)
- Product Assurance:
  - FY00$K = 15% x (Ground Segment Software)
  - SE = 25% (assumed)
- Integration & Test:
  - FY00$K = 24% x (Ground Segment Software)
  - SE = 25% (assumed)

Figure 3-1 Ground Segment Cost Estimating Equations

Point Estimate

Using the deterministic roll-up approach, a point cost estimate is developed by inserting the input variables into the CERs, and summing them, as shown below.

Ground Segment (FY00$K)

	Cost
Ground Segment Software (SW)	22000
Facilities (FAC)	3960
Equipment (EQ)	17820
Logistics	3300
Systems Level	
Management	3960
Systems Engineering	6600
Product Assurance	3300
Integration and Test	5280
Total Ground Segment and Operations	**66220**

Now, if the cost analyst chooses to ignore cost modeling uncertainty, then the conclusion is that the total Ground Segment cost estimate is approximately $66.2M (FY00).

Cost Risk Approach

A better way to develop this cost estimate is to properly account for cost modeling and technical uncertainty by quantifying the probability distributions of the input variable and the CERs, and then summing the WBS elements statistically through Monte Carlo simulation.

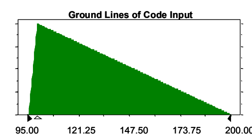
CER Input Distribution

The CER input distribution can be arrived at through consultation with engineers and other experts. This example uses a triangular distribution with a minimum value of 95 KSLOC, a most likely value of 100 KSLOC and a maximum value of 200 KSLOC as shown below.

- Ground Software (KSLOC)

Triangular distribution with parameters:

Minimum	95.00
Likeliest	100.00
Maximum	200.00



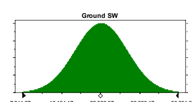
CER Output Distributions

The CER output distributions are dependent on the value of the input (which determines the mean) and the standard error, or standard percent error (which determines the standard deviation) associated with each CER. In this example the output distributions are assumed to be normal. The illustrations below show the CER distributions that result from using their mean input values. For example, the mean of the Ground Software input distribution is (95 + 100 + 200) / 3 = 131.67. This value is then inserted into the Ground Segment Software CER, 220 x 131.67 = 28,966.67. Thus, the mean of the Ground Segment Software CER distribution, evaluated with an input of 131.67 KSLOC, is 28,966.67. Additionally, the standard deviation of this distribution is 25% of the mean, or 7,241.67. Subsequently, the Facilities CER is evaluated using an input value of 28,966.67. This distribution then has mean 18% x 28,966.67 = 5,214 and standard deviation 25% x 5,214 = 1,303.5. The remaining CER distributions are determined in a similar manner.

- Ground Segment Software

Normal distribution with parameters:

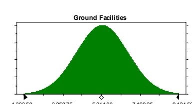
Mean	28,966.67
Standard Dev.	7,241.67



- Facilities

Normal distribution with parameters:

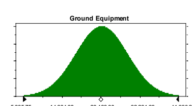
Mean	5,214.00
Standard Dev.	1,303.50



- Equipment

Normal distribution with parameters:

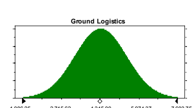
Mean	23,463.00
Standard Dev.	5,868.75



- Logistics

Normal distribution with parameters:

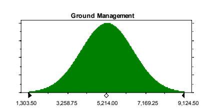
Mean	4,345.00
Standard Dev.	1,086.25



- Program Management

Normal distribution with parameters:

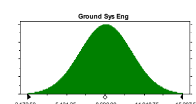
Mean	5,214.00
Standard Dev.	1,303.50



- Systems Engineering

Normal distribution with parameters:

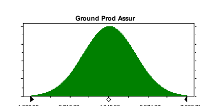
Mean	8,690.00
Standard Dev.	2,172.50



- Product Assurance

Normal distribution with parameters:

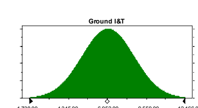
Mean	4,345.00
Standard Dev.	1,086.25



- Integration & Test

Normal distribution with parameters:

Mean	6,952.00
Standard Dev.	1,738.00



Correlation Coefficients

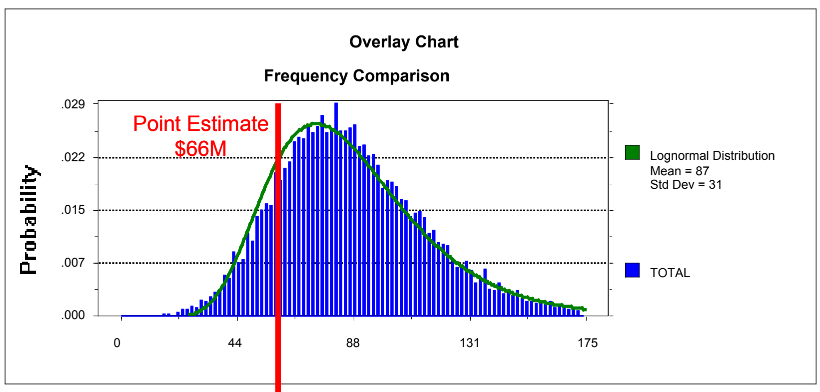
In order to properly account for the uncertainty of the combination of CER uncertainties, the correlation between each CER must be estimated. The correlation table below shows all correlations used in the FireSat Ground Segment cost estimate.

Table 3-1 - FireSat Ground Segment Correlation Matrix

	Ground SW	Ground Facilities	Ground Equipment	Ground Logistics	Ground Management	Ground Sys Eng	Ground Prod Assur	Ground I&T
Ground SW	1.000	0.200	0.200	0.200	0.200	0.200	0.200	0.200
Ground Facilities		1.000	0.200	0.200	0.200	0.200	0.200	0.200
Ground Equipment			1.000	0.200	0.200	0.200	0.200	0.200
Ground Logistics				1.000	0.200	0.200	0.200	0.200
Ground Management					1.000	0.200	0.200	0.200
Ground Sys Eng						1.000	0.200	0.200
Ground Prod Assur							1.000	0.200
Ground I&T								1.000

Monte Carlo Simulation

Once all the CER and input variable uncertainties are correctly quantified, and a correlation matrix is specified, it is then possible to perform a Monte Carlo simulation of the cost estimate. The result of a simulation using Crystal Ball® is shown in Figure 3-2 below.



Statistics:	Value
Trials	10000
Mean	87
Median	84
Mode	---
Standard Deviation	31
Variance	979
Skewness	0.69
Kurtosis	3.67
Coeff. of Variability	0.36
Range Minimum	1
Range Maximum	236
Range Width	235
Mean Std. Error	0

Percentile	Value
0%	1
10%	51
20%	62
30%	70
40%	77
50%	84
60%	92
70%	101
80%	112
90%	130
100%	236

Figure 3-2 - Result of FireSat Ground Segment Monte Carlo Simulation

At this point, instead of estimating the *cost* of the FireSat Ground Segment, we've instead estimated the *probability distribution of the cost* of the FireSat Ground Segment.

Some interesting things to point out are:

1. The mean, or expected value, of the cost estimate is $87M.
2. The median, or 50th percentile, of the cost estimate is $84M.
3. The standard deviation of the cost estimate is $31M.

4. The cost distribution is well approximated by a lognormal distribution with mean and standard deviation given above.
5. The deterministic point estimate, $66M, underestimated the expected cost by approximately $21M, or about 24% (=21/87).
6. The table of percentiles enables a decision-maker to decide how much to budget for this program in order to satisfy any desired probability of budgetary success. For example, if the decision-maker wishes to ensure an 80% chance of avoiding a budget shortfall, he should set his budget for the program at $112M.
7. By the way, if the decision-maker were to set his budget at the deterministic cost estimate of $66M, he would have only a 24% chance of avoiding a budget shortfall. Correspondingly, budgeting at this value would ensure the decision-maker a 76% chance of a budget shortfall!

References

[1] Wertz, James R. and Larson, Wiley J., *Space Mission Analysis and Design, 3rd Edition*, Microcosm Press and Kluwer Academic Publishers, 1999.

[2] Anderson, T.P., "Cost Risk Tutorial," *The Aerospace Corporation*, Space Systems Engineering Risk Management Symposium, Manhattan Beach, CA, February 2004.

4. How Much Risk is in a Cost Estimate?

Timothy P. Anderson
The Aerospace Corporation

Introduction

Senior acquisition decision-makers usually desire to know a few things about cost estimates.

1. One questions is: "How much 'risk' is in the estimate?" Translation: How many dollars are in the estimate to guard against risky events happening?
2. A similar sounding, but separate question is: "How 'risky' is the estimate?" Translation: If the budget is set at a certain value, what is the likelihood of an overrun?
3. And a third question is: "How much 'management reserve' is in the estimate?" Translation: How many dollars are in the estimate for management reserve, over and above dollars expected to be needed for acquisition and risky events?

How Many "Risk Dollars" Are in the Estimate?

This question can have multiple answers. It requires a baseline cost estimate against which to compare. For example, "The baseline estimate is $100M. We've estimated $120M, therefore, our estimate contains $20M to cover potential risky events." But, what is the baseline scenario that produces the baseline cost estimate?

At least three possible baselines exist. The contractor has a baseline and the program office has a baseline. In addition, some independent cost agencies produce an independent technical assessment (ITA). The ITA provides an independent, more realistic, look at the cost drivers. An explanation of the differences follows:

1. Contractor proposal: This is the program as the contractor sees it. The technical description reflects the contractor's best guess of the cost drivers such that the stated minimum government requirements are met. ***A rough, first cut, baseline.***
2. Program office baseline: This is the program as the program office sees it. The technical description reflects the system that the program manager thinks is manageable from a cost, technical, schedule, and budget perspective. ***A manageable, albeit unlikely, baseline.***
3. Independent technical assessment: This is the program as seen by realistic-minded outside observers. The technical description reflects the "likely-to-be" program, that will result after predictable engineering changes, requirements changes, schedule changes, etc. **A realistic, likely-to-be, baseline.**

Every scenario is different, and leads to a different cost estimate. The amount of risk dollars in the estimate depends on the baseline against which we are comparing. For example, suppose four estimates are produced. Each estimate uses the same set of CERs, but the first estimate uses the contractor-proposed input variables; the second estimate uses the program office inputs; the third estimate uses the ITA inputs; and the fourth estimate, the ICE, is a fully risk-adjusted estimate, developed using Monte Carlo simulation with randomly varying inputs and outputs. Suppose the results are:

- Contractor proposal = $230M

- Program office baseline = $300M
- Independent technical assessment = $335M
- Independent cost estimate (ICE) mean = $346M

Then, the amount of risk dollars in the ICE mean estimate, compared to each of baselines is:

- ICE vs. contractor proposal: $116M
- ICE vs. program office baseline: $46M
- ICE vs. independent technical assessment: $11M

So, how many risk dollars are in the estimate? It depends on the choice of the baseline. If we desire to compare the ICE to the contractor proposal, then the estimate contains $116M for risky events. In this event, examples of risky events include engineering changes, requirements changes, test failures, etc. The program office baseline is usually somewhat more realistic than the contractor proposal from a total cost perspective. This is because the program office will include costs that the contractor can ignore, such as government systems engineering and program management, government-furnished equipment, and perhaps some anticipation of engineering and requirements changes. Comparing the ICE to the program office estimate, the ICE contains $46M to cover risky events. This is less than the amount of risk dollars relative to the contractor proposal since the program office has already assumed some of these events will occur. Finally, if we compare the ICE to the ITA, then the estimate contains only $11M for risky events, since the ITA has already assumed most of the risky events will occur.

The Risk-Adjusted Estimate

A properly developed independent cost estimate, with realistic cost drivers, in which both cost estimating and technical uncertainty have been quantified and included in the process, is known as a risk-adjusted estimate. In other words, if we've done everything right, modeled CER and cost driver uncertainty, and produced a cost probability distribution, then we can use it as a benchmark, and quantify risk dollars relative to any other baseline cost estimate. ***All independent cost estimating agencies should be striving to produce risk-adjusted estimates.***

Figure 4-1 illustrates the quantification of risk dollars using a risk-adjusted estimate as the benchmark; and contractor, program office and ITA estimates as baselines.

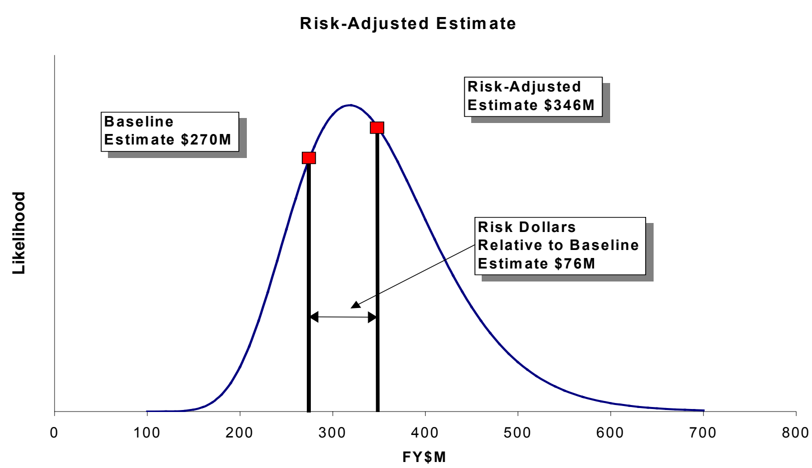


Figure 4-1 - Risk-Adjusted Estimate

Since the risk-adjusted estimate is really a probability distribution, then it is necessary to choose a value along the distribution for use in comparing other types of estimates. The natural choice is the expected value, or mean, of the distribution. So, going back to the earlier illustration, if the mean of the risk-adjusted estimate is $346M, then, for example, it contains $11M risk dollars relative to the ITA. In other words, the difference between the mean of the risk-adjusted estimate and the ITA estimate represents the amount of risk in the estimate, *relative to the ITA*. Similarly, it contains $46M risk dollars *relative to the program office estimate*. Thus, if a decision-maker should ask, “You’re estimate is $346M. How much of that is earmarked for risk?” You have an easy answer: “Sir, relative to the independent technical assessment of $335M, we’ve booked an additional $11M to cover risks that might reasonably occur.” Moreover, if the two estimates are listed side-by-side, it is easy to identify the amount of risk dollars allocable to each WBS element, and, since we’ve quantified the input variable uncertainty, we can also explain *why* a certain WBS element contains risk. For example, you might say, “The reason there is an additional $5M risk dollars for software is because, while the software code count is most likely to be 500 KSLOC, there is some likelihood that it might double in size, according to our software engineering assessment.”

How “Risky” is the Estimate?

This is a different question. In the previous section we discussed the amount of “risk dollars” in an estimate. Now we look at it from a different angle. The real question here is “If we set the budget at the expected value of the risk-adjusted estimate, what is the probability of a budget overrun?” A good name for this type of risk is “budget risk.”

Every budget contains risk. The risk is that the budget is too low. The amount of risk contained in any budget is measured by the probability of overrunning that particular budget.

Budget risk has a direct correspondence to the percentiles of the risk-adjusted estimate’s probability distribution. Consider the risk-adjusted estimate shown in Figure 4-1. Recall that the mean of this distribution is $346M. Notice that this corresponds to the 49^{th} percentile of the probability distribution. This means that the probability the true cost will be less than or equal to $346M is 49%. The obvious implication is that there is a 51% chance that the true cost will be *greater* than $346M. Therefore, if the budget is set at $346M, then the budget risk is 51%, that is, all else being equal; there is a 51% chance of overrun if the budget is set at $346M. Refer to Figure 4-2.

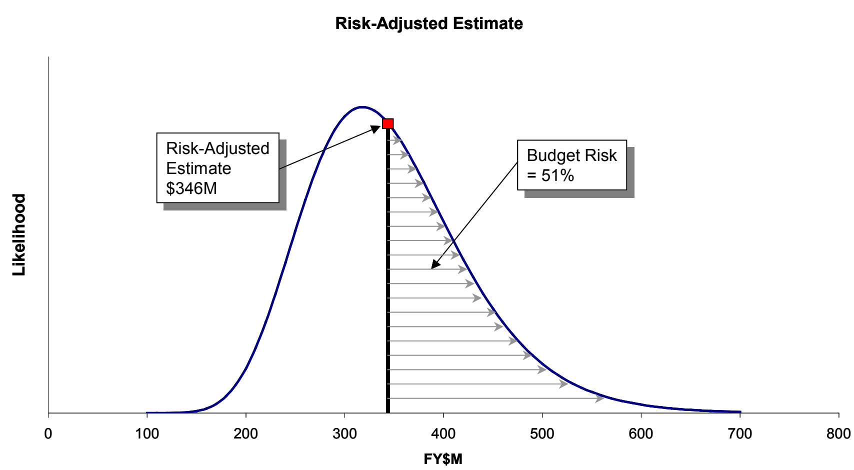


Figure 4-2 - Budget Risk

It is, of course, possible to reduce budget risk. If the decision-maker desires to reduce budget risk to, say, 20%, then he must budget to the 80th percentile of the cost distribution. In this example, he'd have to set his budget at $410M. This example illustrates the tremendous management utility of having a cost probability distribution rather than a simple cost estimate.

In summary, the amount of budget risk in an estimate is simply the area under the curve of the cost probability distribution that lies to the right of the budget amount. The greater the budget, the less the budget risk

How Much "Management Reserve" is in the Estimate?

Management reserve is money that is in the budget, but not earmarked for any specific risk. Now, suppose a risk-adjusted cost estimate has been produced and the budget is set at the expected value of the cost distribution. How much management reserve is in the budget? *NONE!* The expected value of the risk-adjusted cost estimate has just enough money to cover normal acquisition plus *anticipated* risks. If a decision-maker wants management reserve, he'll have to budget at a value that is higher than the expected value of the cost distribution. In other words, the difference between the budget and the expected value of the cost distribution is management reserve. Figure 4-3 illustrates management reserve, assuming the budget is set at some value higher than the risk-adjusted estimate.

Under current government acquisition practices, management reserve is unlikely to be available. If any program manager has management reserve sitting in an account somewhere, it will be swept up by the comptroller for use somewhere else. In practice, therefore, the largest budget anyone can reasonably ask for is the expected value of the risk-adjusted cost probability distribution.

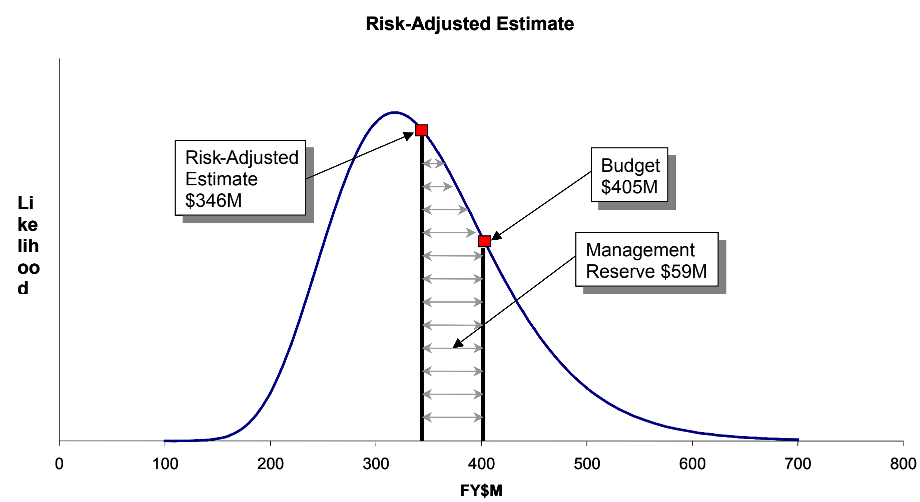


Figure 4-3 - Management reserve

References

[1] Anderson, T.P., "NRO Cost Group Risk Process," *The Aerospace Corporation*, 72nd Military Operations Research Society Symposium, Monterey, CA, June 2004.

Perspectives and Applications

5. Continuous Cost Risk Management at NASA

David Graham
NASA

NASA's New Emphasis

The Bush administration has definitively indicated that a new emphasis for NASA program management was necessary with the appointment and confirmation of Sean O'Keefe as the NASA administrator. The emphasis is to improve budgetary control. A NASA HQ's April 2003 briefing to its Project Management Council quoted the House Staff Director's comment at a recent interchange, "The long series of NASA program over-runs, followed by cancellations, have eroded NASA's credibility – explanations "don't wash" and don't jibe with NPR 7120.5"[1]. (7120.5 is the NASA Policy Requirements (NPR) document for Project and Program Management.)

A rebuilding of credibility is necessary at NASA. Implementing this rebuilding has begun with selecting a new CADRe of visionary and committed managers and empowering them to implement their vision of improved program management. No area of possible improvement is being regarded as out-of-bounds, including improved cost management. The main policy vehicle for instituting a new approach to cost management is NASA's revised Project and Program Management Procedures and Requirements Document, NPD/NPR 7120.5, version "C".

Continuous Cost-Risk Management Perspective

The context for this more rigorous cost, risk and performance management integration process is Continuous Cost-Risk Management[2]. Within CCRM, 12 cost analysis disciplines are treated as an interrelated "system of cost systems" rather than traditional stovepipes. These 12 disciplines are: cost/performance trades (a subset of which is Cost as an Independent Variable or CAIV trades); project definition (NASA Cost Analysis Data Requirements or CADRe); cost estimation; risk assessment and analysis; translation of risk into cost impacts for cost-risk probability distribution determination; Request for Proposal (RFP) data requirement development and dissemination; source selection cost proposal evaluation; post-award government/contractor meeting for cost-risk reporting understanding (Earned Value Management (EVM) Integrated Baseline Review (IBR) when appropriate); proactive cost-risk monitoring and management; updating of life cycle cost estimate including cost-risk probability distribution updates; post-contract data analysis; and, updating cost and cost-risk databases and models with new data points.

The Cost-Risk Management Problem

Before describing Continuous Cost-Risk Management in any real detail, I think it would be instructive to view the cost-risk management environment in terms of the overall problem for which CCRM is the author's proposed solution. I will borrow from the field of physics its 2nd Law of Thermodynamics (physicists, please cut this cost analyst some slack) and from the field of evolutionary biology (same request from the biologists) to develop a metaphor for the conditions under which cost-risk management must exist.

From the 2nd Law of Thermodynamics I would like to characterize the general nature of project management in terms of *entropy*. My working definition for entropy is simply, 'for a closed system, order tends towards disorder'. So, without some intervening action, chaos eventually will rule project management. Perhaps a project familiar to the reader resembles this remark?

As a counterforce to entropy nature has produced living systems. Living systems behave differently than entropic systems - *they evolve*. Evolution is a counterforce to entropy. Evolution involves processing information in the form of feedback to initiate and sustain progress. Feedback is crucial to evolutionary development. In fact, feedback can be seen as being the fuel of evolution producing the counterforce to entropy, negative entropy[3]. Here, obviously for evolution to occur, negative entropy is a good thing.

To continue my metaphor I need to describe the four general phases of evolution. The first phase is "pre-equilibrium" and exists whenever positive entropy is greater than negative entropy. The second phase is, you guessed it, "equilibrium". In this phase positive and negative entropy appear to be equal. I say 'appear' to be equal because, if evolution is truly occurring, this is only a temporary phase since the living system is learning from feedback in order to adapt to any new conditions and the first step is to halt the tendency to disorder - kind of like treading water. The third phase of evolution is "change". The living system has changed slightly in adapting to the new conditions but still is recognizable however slightly different. The fourth and final phase of evolution is "transformation" where the living system has adapted to the new environment for survival and, in this phase, is much less recognizable from its earlier appearance, behavior and results.

What's any of this got to do with cost-risk management? Here's the punch line: a good cost-risk management system is a *living system* that is fueled by feedback in order to improve. Let me illustrate the four phases of a cost-risk management system's evolution, from pre-equilibrium, equilibrium and change through transformation applying the cumulative distribution function as the metric.

Pre-Equilibrium Phase

In the beginning of the Pre-Equilibrium phase, the government's estimate (in reality a project life cycle cost estimate (LCCE) distribution of possible costs e.g., cumulative distribution function (CDF)) as illustrated in Figure 5-1, indicates the selected confidence level dollar value (e.g., 50% confidence level in Figure 5-1). This CDF represents the best result from a cost estimate and cost-risk assessment as to the cost of a particular project.

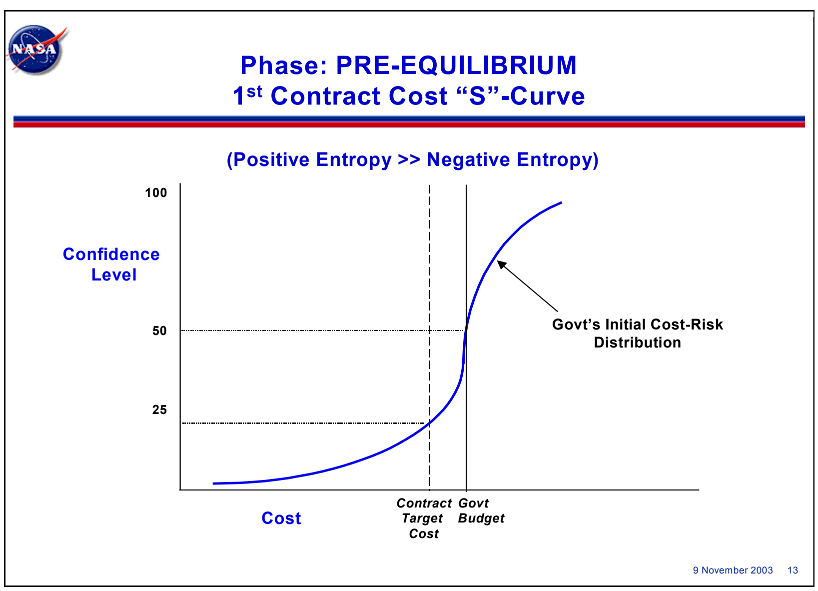


Figure 5-1

As the project proceeds, as illustrated in Figure 5-2, it becomes clear that control over the risk impacts to cost is not successful as the CDF shifts to the right and becomes less vertical. This behavior is indicative of risks not being retired and also increasing their negative cost effects.

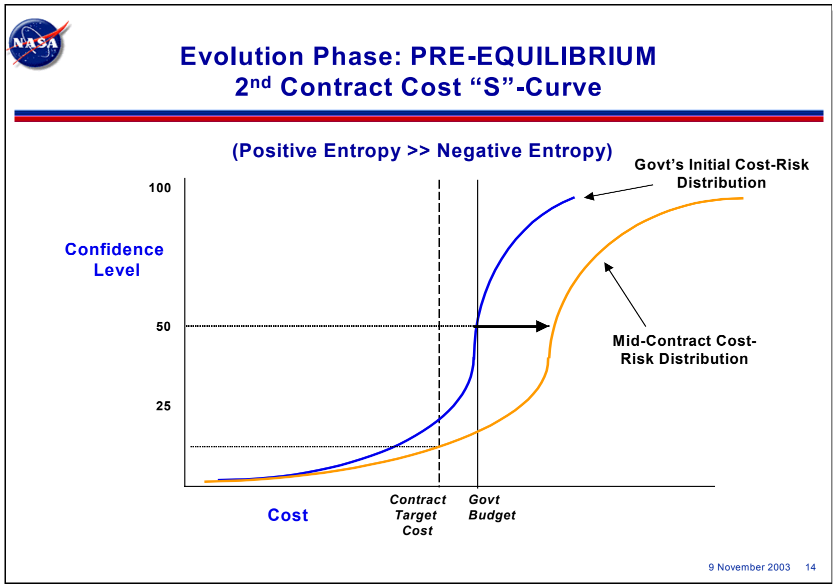


Figure 5-2

At the third LCCE update in Figure 5-3, it is apparent that the risks have not been retired and, in fact, are continuing to have a deleterious effect on the costs. The CDF has shifted further to the right and has even gotten 'flatter' indicating that not only were the basic assumptions of the 50% cost estimate wrong but the assessments of the risks were also understated.

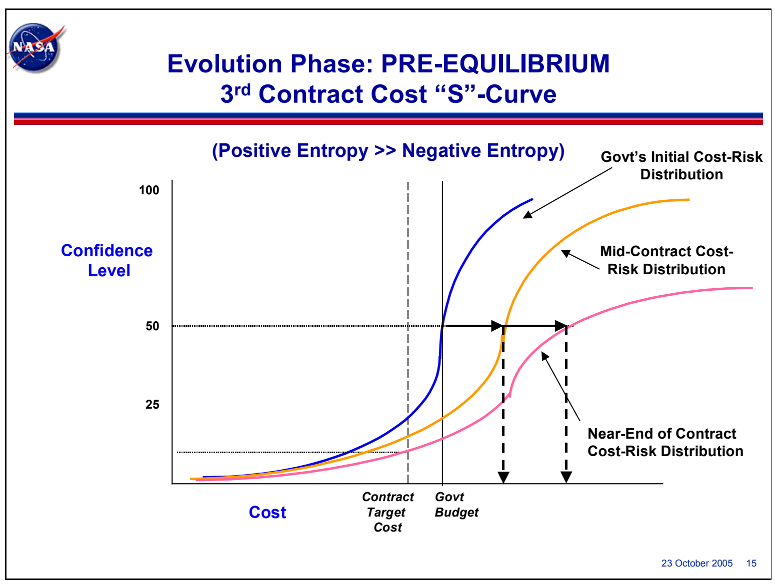


Figure 5-3

If this looks like any programs with which you may be familiar it is strictly coincidental, however, cost behavior such as that illustrated is consistent with a Pre-Equilibrium evolutionary state where there really is no cost-risk management system learning from potential feedback.

Equilibrium Phase

If the underlying evolutionary situation is the second phase, that is, Equilibrium, the CDF behavior illustrated in Figure 5-4 is expected. In this case, the government's CDF estimate begins in the same position as in the Pre-Equilibrium case.

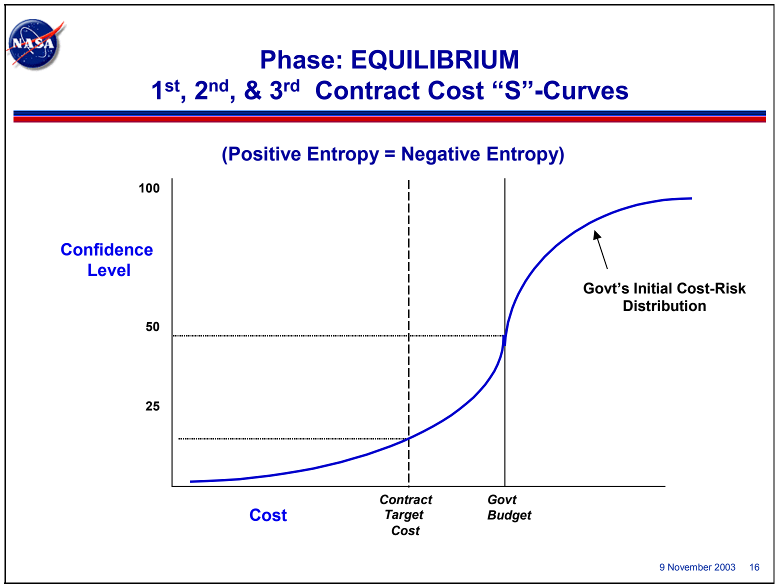


Figure 5-4

However, the 2nd and 3rd updates to the CDF produce a mirror image of the CDF indicating that a stabilization of cost-risk management has occurred as illustrated in Figure 5-5 and Figure 5-6 below.

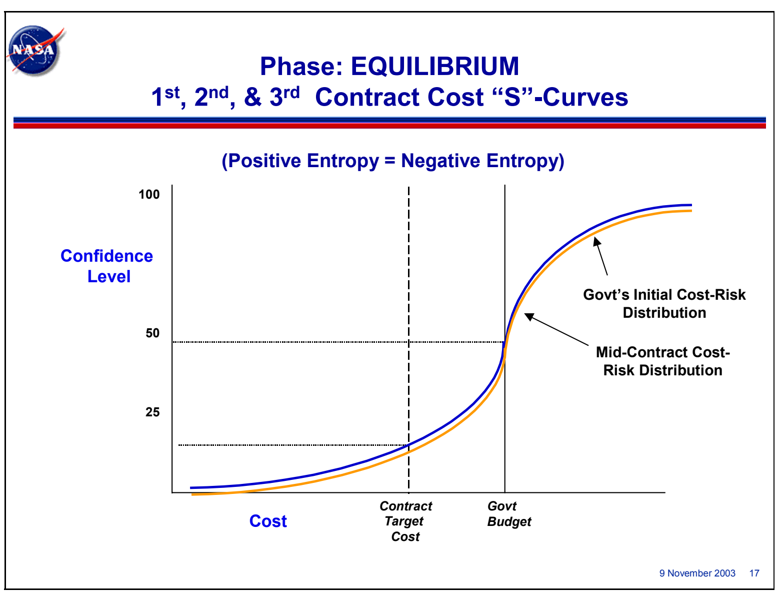


Figure 5-5

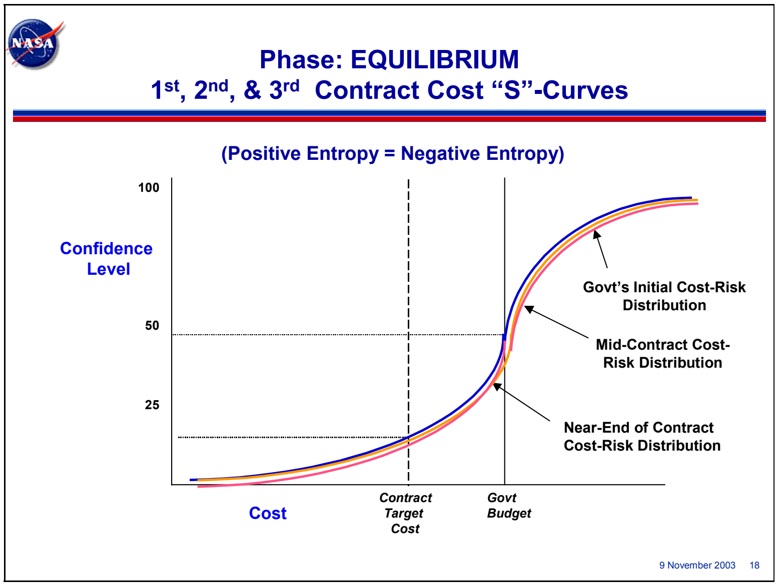


Figure 5-6

Cost behavior such as that illustrated in Figure 5-6 is consistent with an evolutionary state in Equilibrium where the cost-risk management system is beginning to learn from potential feedback.

Change Phase

In the third evolutionary phase, Change, the government's initial CDF again starts in the same location as illustrated in Figure 5-7 but in Change, negative entropy is greater than positive entropy.

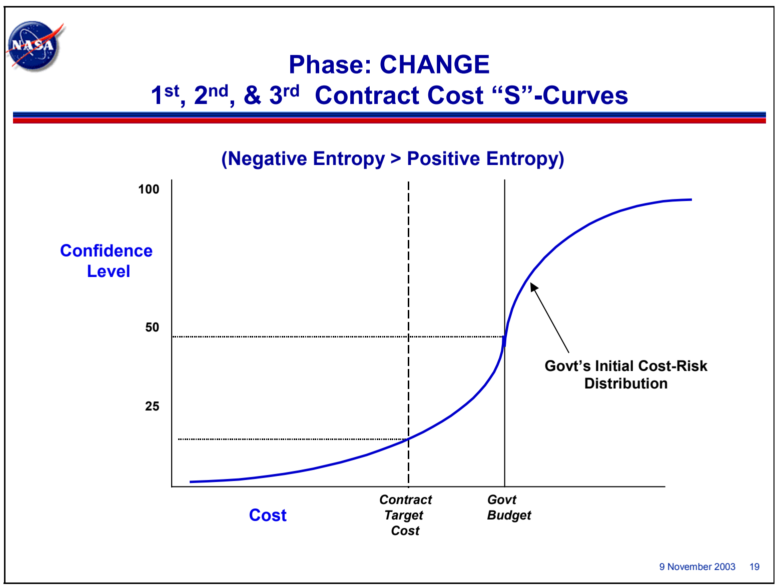


Figure 5-7

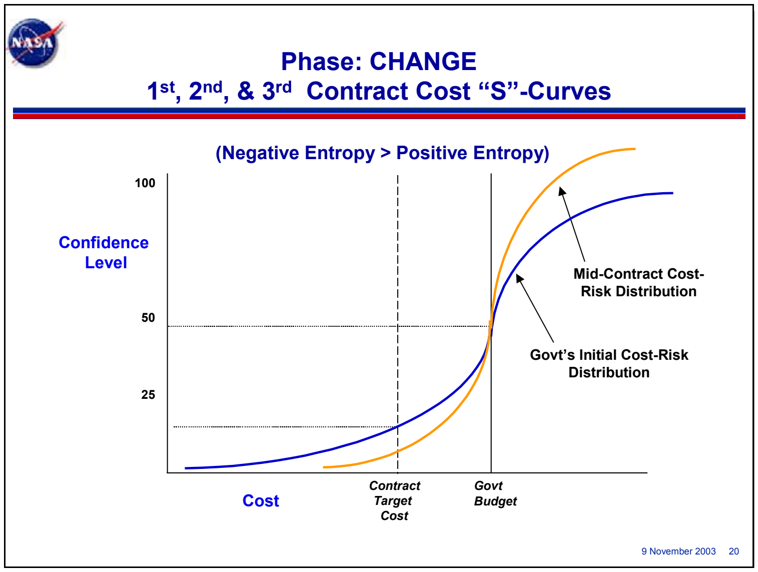


Figure 5-8

The first CDF update indicates a reduction in variance has occurred as illustrated in Figure 5-8. This is identified by the change in relative steepness in the updated CDF relative to the initial CDF. This indicates that the risks and cost-risks are being retired. The CDF is the metric that indicates this by a vertical shift in its position relative to the initial range represented by the initial CDF.

The second CDF update, illustrated in Figure 5-9, shows a continuation of the increases in steepness of the CDF, indicating a reduction in the possible range of probable costs (variance reduction) due to the success of the cost-risk management system. The cost-risk management system is utilizing feedback about the effects of the risks creating the opportunity for project management to utilize its information content to react to risk challenges successfully. Even though the initial 50% estimate has not changed through two updates, the variance has changed indicating success in reducing the negative effects of risk on cost.

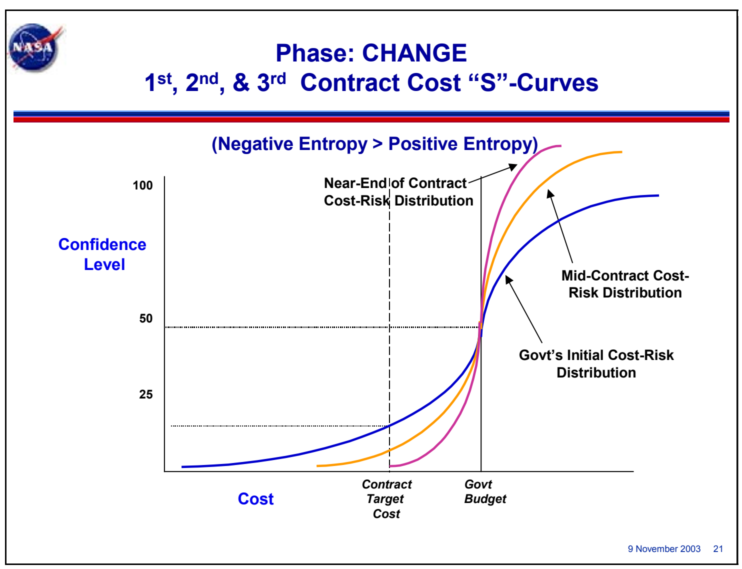


Figure 5-9

Transformational Phase

In the final example of evolutionary development, Transformational, we start again with the same initial CDF as illustrated in Figure 5-10.

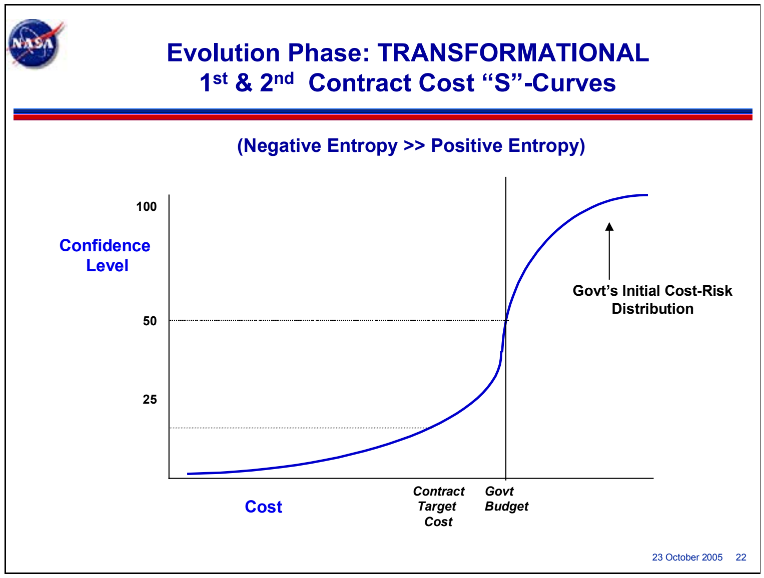


Figure 5-10

By the time of the first update, as depicted in Figure 5-11 below, not only has the CDF gotten steeper relative to the initial CDF, it has shifted to the left, indicating so much success in retiring risk that not only has the range of possible costs been reduced, the 50% estimate has now been reduced.

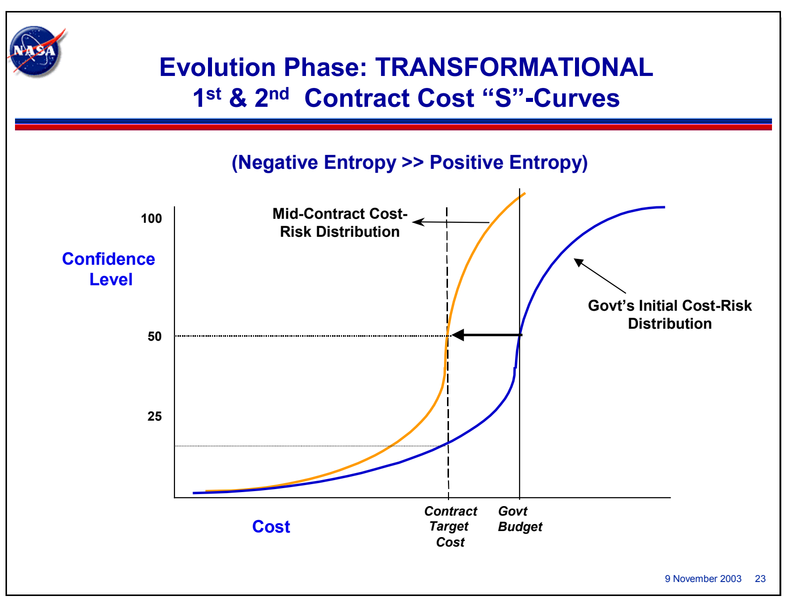


Figure 5-11

As illustrated in Figure 5-12 below, the second CDF update continues this trend of ever-steepening CDFs and shifting to the left even more. The cost-risk management system is producing an optimum level of actionable information from the feedback mechanisms in place such that project management can react so quickly to the possible negative trends that they never materialize. Such insight is being produced that actions taken are effective in exactly the right places at exactly the right times to make these positive changes occur.

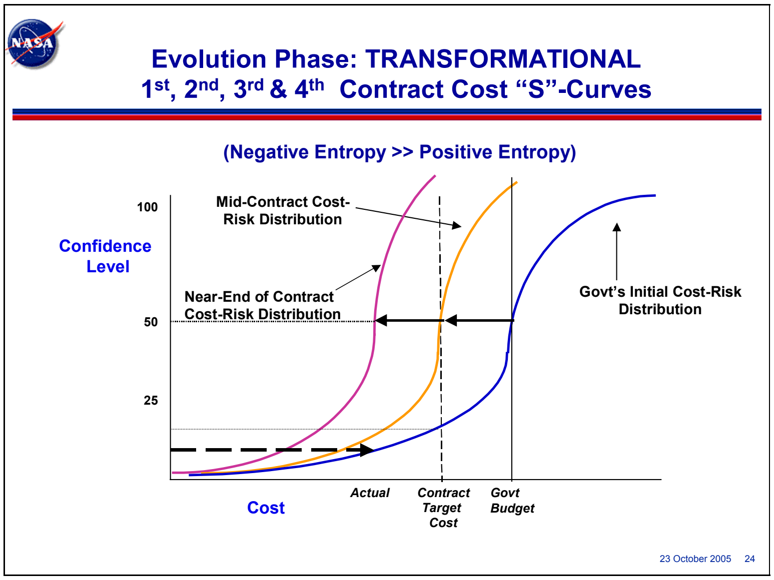


Figure 5-12

In Figure 5-13 below, a truly idealized situation is depicted where, at the end of the effort, the CDF is a vertical line with no variance whatsoever due to the cost being an "actual" at this point.

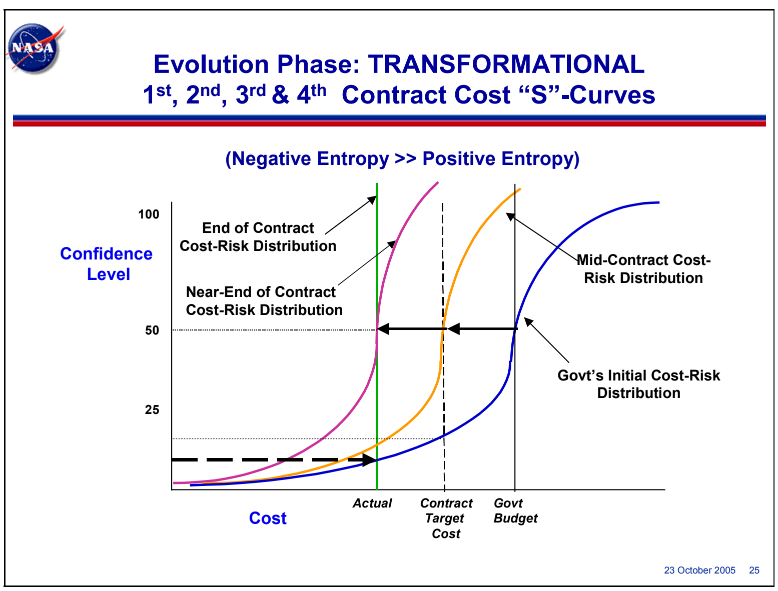


Figure 5-13

Furthermore, the actual cost is much less than the original government CDF estimated the cost to be at the 50% level. The implications of a situation like this occurring are truly profound. If our cost-risk management systems were this efficient and effective over many projects and programs, the total obligation authority appropriated by Congress would support more programs. However, over time, this might just result in fewer dollars being appropriated for the same number of programs or, in a more positive light, more dollars being appropriated for a greater number of programs since confidence in NASA being able to manage the budgets provided by Congress would increase which is a goal of the current NASA Administrator[7].

So, how do we get from a situation of Pre-Equilibrium to Transformational as I have described them? NASA project and program management is exploring the implementation of Continuous Cost-Risk Management to evolve its acquisition management to a situation that more closely resembles the Transformational than the Pre-Equilibrium state.

Continuous Cost-Risk Management

In order to meet the space project cost challenges for the next decade and beyond, NASA cost management processes must evolve from traditional methods to modes that ensure congressional confidence. The new focus for NASA project cost management will be *cost-risk management*. This change in focus will also facilitate the transition from implementing cost management as a set of “stovepipe” cost disciplines to an integrated “system of cost systems”. In reality, cost management is a continuum of related cost activities and involves three main steps that are linked together through a shared set of project risks. Cost management, in effect, is the management of cost-risk and can be characterized as “Continuous Cost-Risk Management”.

Feedback is essential to the transformation of cost management into a dynamic, continually reacting system where focused reporting of metrics on high-risk drivers alert the project manager that a negative cost trend has been identified and requires action. The three stages of this Continuous Cost-Risk Management: *preparation* of cost-risk feedback; *developing* cost-risk feedback; and, *applying* cost-risk feedback, occur at different points in time during an acquisition phase and involve the collaboration among cost estimators, project engineers, project managers, procurement analysts and Earned Value Management (EVM) specialists in managing the challenges presented by the risks. Cost management is not a grouping of unrelated stove-piped cost activities but is a "system of cost systems" based on viewing 12 cost activities normally treated as stovepipes as a "continuum" of activities interconnected through risk. CCRM repeats in most acquisition phases.

The first stage in Continuous Cost-Risk Management, *preparing* for cost-risk feedback, involves NASA project teams doing five main activities: cost/performance trades (e.g., Cost as an Independent Variable (CAIV)); developing a definition of the program (e.g., NASA Cost Analysis Data Requirement (CADRe)); producing a reference point cost estimate; assessing risks; and, assessing the cost impacts due to risks in deriving a range of possible costs (e.g., probability density function (PDF) and cumulative distribution function (CDF) or “S”-curve). Participants in the *preparing* for cost-risk feedback stage of CCRM are mainly cost estimators, project engineers and project managers. This represents the starting point for cost-risk management. From this point forward the challenge will be in managing to the cost level chosen, no matter what cost-risk margin has been included.

The second stage in Continuous Cost-Risk Management is *developing* the cost-risk feedback to manage the cost-risks and involves NASA project teams doing three main activities: writing cost-risk data requirements into solicitation documents; evaluating bidder responses during source selection; and, meeting with the selected contractor personnel responsible for managing the cost-risks post-award (for details see the NASA Cost Estimating Handbook at www.ceh.nasa.gov). Participants in *developing* cost-risk feedback are the cost estimators, project engineers, project managers, procurement analysts and EVM specialists.

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[7] There is an assumption being made here about the state of our cost models that is that today’s models are based on data from projects managed *pre-CCRM*. *Post-CCRM* data will reflect actual costs lower than that experienced in the pre-CCRM timeframe resulting in estimates lower than that being produced by today’s models. Therefore, the ability to utilize funds not used (due to underruns) will be a temporary phenomenon.

The third stage in Continuous Cost-Risk Management is *applying* the cost-risk feedback for managing costs and involves NASA project teams doing four main activities: utilizing cost-risk feedback data (e.g., EVM Cost Performance Reports, TPM reports, etc.) for project management; applying updated total project estimate "S"-curves for cost-risk progress status and estimates at completion; applying end-of-contract cost-risk data to calibrate follow-on contract estimates; and, applying final cost and cost-risk data to update cost databases and cost models. If the first two stages in cost-risk management, *preparing* for cost-risk feedback and *developing* cost-risk feedback, have been properly accomplished, the cost-risk feedback from the required data will contain the highest quality information possible for managing risk and cost-risk. Participants in *applying* cost-risk feedback are primarily project engineers, project managers and EVM specialists with cost estimator involvement during cost/performance trades (if required), and updating "S"-curves, databases and cost models.

Continuous Cost-Risk Management, with preparing, developing and applying cost disciplines, is illustrated in Figure 5-14 below. When fully implemented initially, CCRM should produce at least the Equilibrium evolutionary phase of cost-risk management and may possibly produce results as expected in the evolutionary phase of Change.

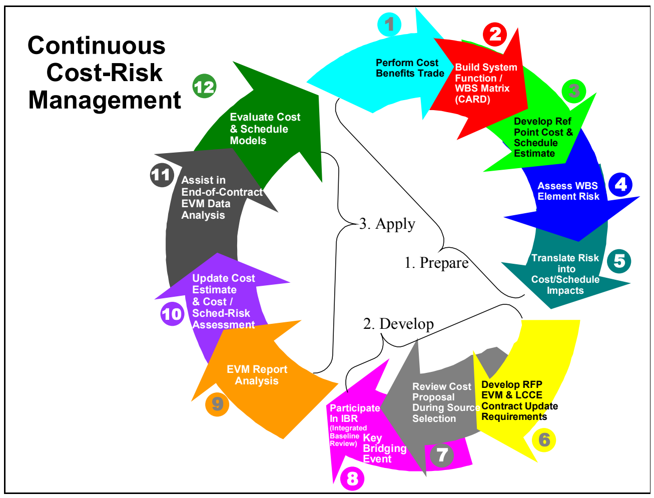

Figure 5-14

NASA Project Cycle Acquisition Phases: Roles & Responsibilities

In the early acquisition phases, that is, pre-Phase A and Phase A, the *Set Up* stage of CCRM will predominate. In Phases A, B & C/D, however, the *Preparing, Developing, and Applying* paradigm of Continuous Cost-Risk Management is applied as illustrated in Figure 5-15 below. Cost estimators play the dominant role during the *Preparing* step of Continuous Cost-Risk Management, share a significant role during the *Developing* step, with EVM specialists playing the dominant role and cost estimators playing a minor role during the *Applying* step.

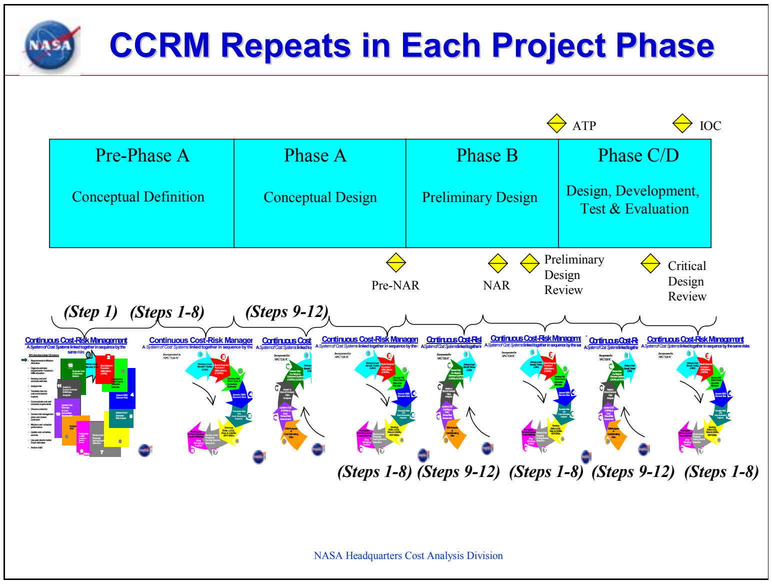

Figure 5-15

Pre-Phase A (Conceptual Definition)

In Pre-Phase A, due to the lack of a stable system configuration and no hardware contractors fully under development phase contracts, only the *Preparing and Developing Stages* for cost-risk feedback (with most of the emphasis on cost/performance trades aspects of CCRM) is applied. However, in each subsequent phase, the full CCRM can be implemented. The Field Center SMOs, CFOs, and cost groups are responsible for preliminary cost estimates and cost support to conceptual design activities. The Mission Directorate, IPAO and HQs Cost Analysis Division will primarily maintain cognizance in Pre-Phase A with HQs Cost Analysis Division providing strategic guidance for cost estimating processes to include assessment of risk for cost impacts. Pre-Phase A is characterized by intense early cost/performance trade-off analyses between requirements and costs, perhaps also Cost as an Independent Variable (CAIV) trades. Basically, through quantifying the effectiveness brought to the potential missions by varying levels of requirements (e.g., alternative level requirements allocation) and costing out each level, an incremental effectiveness/cost “knee-in-the-curve” analysis can be performed (see Figure 5-16 below). The costing of each level of the requirements will incorporate the cost-risk impacts, as well as they can be captured, due to identified risks in the alternative designs. The analysis identifies the point on the curve where little effectiveness is gained for more expenditure of funds. Hopefully, this point achieves at least the minimum measure of effectiveness necessary to move into Phase A. If not, more study is necessary to spiral up to that point. The decision to proceed into Phase A will be made on the basis of technical feasibility, desirability and affordability of the ideas derived from these early cost/performance trades.

Optimization Curve with "Knee"

Constrained Cost	Solution Cost	Benefit	Group
13700	13700	0.212	1,1,1,1
14000	13700	0.212	1,1,1,1
14500	14400	0.25	1,2,1,1
15000	14900	0.286	2,2,1,1
15500	15300	0.386	2,3,1,1
15700	15700	0.697	1,1,3,1
16000	15900	0.311	1,2,2,1
16500	16300	0.411	1,3,2,1
17000	16800	0.835	1,3,3,1
17500	17300	0.871	2,3,3,1
18000	17300	0.871	2,3,3,1
18500	17300	0.871	2,3,3,1
19000	17300	0.871	2,3,3,1
19500	17300	0.871	2,3,3,1
20000	19800	0.882	1,3,3,2
20500	19800	0.916	3,3,3,1
21000	19800	0.916	3,3,3,1
21500	19800	0.916	3,3,3,1
22000	20300	0.918	2,3,3,2
22500	20300	0.918	2,3,3,2
23000	22800	0.963	3,3,3,2
23500	22800	0.963	3,3,3,2
24000	22800	0.963	3,3,3,2
24500	22800	0.963	3,3,3,2
25000	22800	0.963	3,3,3,2
25500	22800	0.963	3,3,3,2
26000	22800	0.963	3,3,3,2
26500	22800	0.963	3,3,3,2
27000	26800	1.019	3,3,3,3

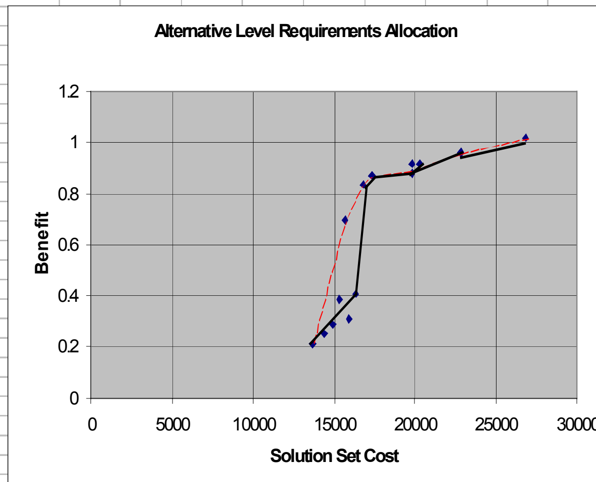

Figure 5-16

Phase A (Conceptual Design) - Initial Application of the Full CCRM

Phase A is the first phase where full Continuous Cost-Risk Management may be implemented. The final cost/performance trades from the end of Pre-Phase A represent the beginning of its full implementation. The *Preparing* stage continues with the effort to build a detailed definition of the project in the form of a streamlined NASA Cost Analysis Data Requirement (CADRe). In general, a NASA CADRe is a technical description of the project in terms useful to cost estimators for developing a Project Life Cycle Cost Estimate (PLCCE) or an Independent Cost Estimate (ICE). Cost organizations assist in developing a NASA CADRe but it is owned and signed by the Project Manager. Contracts may be let at this time to assist in these *Preparing* stage steps to readdress and firm up the mission concept into a Mission Needs Statement (MNS) and ensure that the project justification and practicality are sufficient to warrant a place in NASA's budget. The Request for Proposal (RFP) for entry into Phase A then should contain solicitation direction to potential bidders on risk and cost-risk identified during pre-Phase A for tracking, measurement (perhaps with Earned Value Management (EVM)) and incorporation into the development of a preliminary NASA CADRe and an IPAO Life Cycle Cost Estimate (LCCE). Data Requirement Descriptions (DRDs) for feedback through EVM Cost Performance Reports (CPR), LCCEs, CADRe's, Probabilistic Risk Assessment (PRA) Plans and Reports, Financial Management Reports (533 M&Q), Integrated Master Schedule/Integrated Master Plans (IMS/IMP) and Reports, Risk Management Plans and Reports, a NASA-unique WBS element-level cost data collection system for future cost estimating and updating the NASA CADRe and the Work Breakdown Structure (WBS), would reflect the implementation of Continuous Cost-Risk Management requirements through narratives and interrelationships between DRDs. The contract award or the Phase A contract would go to the bidder who, in part, addressed these contract data requirements most adequately. A post-award meeting would be held with the winner to ensure his project managers understood these data requirements (e.g., the Integrated Baseline Review if EVM was on contract). These steps represent the *Developing* stage of Continuous Cost-Risk Management. The third stage of Continuous Cost-Risk Management, *Applying* cost-risk feedback, would involve analysis of the EVM reporting (if required) and would help in finalizing a formal Mission Needs Statement (MNS), the NASA CADRe, the project LCCE and satisfying the NASA-required independent cost estimate (ICE). Information in EVM reports would help update cost models used in developing the LCCE. Additionally, probabilistic cost/schedule risk analysis for the LCCE would be tied to PRA-identified risks plus programmatic and management risks. In preparation for entering into Phase B, and for budgetary purposes, the Field Center, Mission Directorate and IPAO will reconcile to one probabilistic estimate, in a meeting co-chaired by Deputy Chief Engineer and HQs Cost Analysis Division, for a recommended cost position to the Agency PMC.

Phase B (Preliminary Design)

Phase B is the second phase where Continuous Cost-Risk Management can be fully implemented and it begins with a reassessment of the requirements within the context of cost/performance trades. As these trades are updated they form the basis for an update to the systems engineering evolutionary requirements-to-functions allocation process. In like manner, the rest of the *preparing* for cost-risk feedback step of CCRM is updated, that is, the NASA CADRe, reference point estimate, risk assessment and cost-risk impacts due to risk. The beginning of Phase B represents the first time that the NASA project team has enough information to complete the *preparing* step itself. This ability sets up the next CCRM step, *developing* cost-risk feedback, with the writing of the data requests in the Phase B RFP. The NASA project team now has identified the top risks within the WBS elements and identifies them to the potential bidders in the RFP data requests with the same CCRM-reflected DRDs as in the Phase A RFP. The winning contractor is selected in part based on their approaches in addressing these cost-risk data requests in their proposal and a meeting held with him to ensure a valid baseline and understanding of the cost-risk reporting requirements. If EVM is required on the contract this meeting is called an Integrated Baseline Review (IBR).

After completion of the IBR, the *applying* step of Continuous Cost-Risk Management commences with the delivery of Cost Performance Reports (CPR) containing the cost and schedule performance management aspects of cost-risk feedback. Updates to the cost/performance trades are accomplished, if necessary, based on Project Manager actions required due to cost performance variances and trends reported in the CPRs. Updates to the NASA CADRe and LCCE are delivered in accordance with the contract and/or in response to cost/performance trade updates. At the end of the effort, actual costs and additional data provided in the CPRs and other contractually required reports are compiled and are the basis for updates to the cost and cost-risk databases and models for use in the development of the end-of-Phase B LCCE and ICE. At this point in the life cycle of the project, the LCCE and IPAO ICE would be based on increased detail eventually down to the major assemblies and component levels. Again, probabilistic cost/schedule risk analysis for the LCCE and ICE would be tied to PRA-identified risks plus programmatic and management risks. In preparation for entering into Phase C, and for budgetary purposes, the Field Center, Mission Directorate and IPAO will reconcile to one probabilistic estimate, in a meeting co-chaired by Deputy Chief Engineer and HQs Cost Analysis Division, for a recommended cost position to the Agency Program Management Council.

Phase C/D (Design, Development, Test and Evaluation)

Phase C/D is the third phase during which Continuous Cost-Risk Management can be fully implemented and it repeats the *Preparing, Developing* and *Applying* stages of Continuous Cost-Risk Management just as in Phase B. As the project proceeds through Design, Development, Test and Evaluation, the NASA CADRe is updated as necessary to reflect major engineering and requirements changes along with associated updates to the reference point estimate (in conjunction with the EVM specialists tracking the cost trends in the EVM reports), risk assessments and cost-risk impacts. Since the end of Phase C/D represents the completion of project development, there is much to be gained from exploiting the cost, risk and cost-risk knowledge captured via EVM and CADRe documents during development for improving cost and cost-risk databases, cost models and, ultimately, estimates on future projects.

Feedback Within Continuous Cost-Risk Management

The flow of cost-risk feedback information not only flows in a simple sequence from step to step in the implementation of CCRM, but also there can and should be a dynamic flow of information between many

CCRM steps during, after and before subsequent efforts as illustrated in Figure 5-17 below. When CCRM implementation reaches this stage of cost-risk management evolution it hopefully can be characterized as being Transformational along with all that is expected at that evolutionary stage.

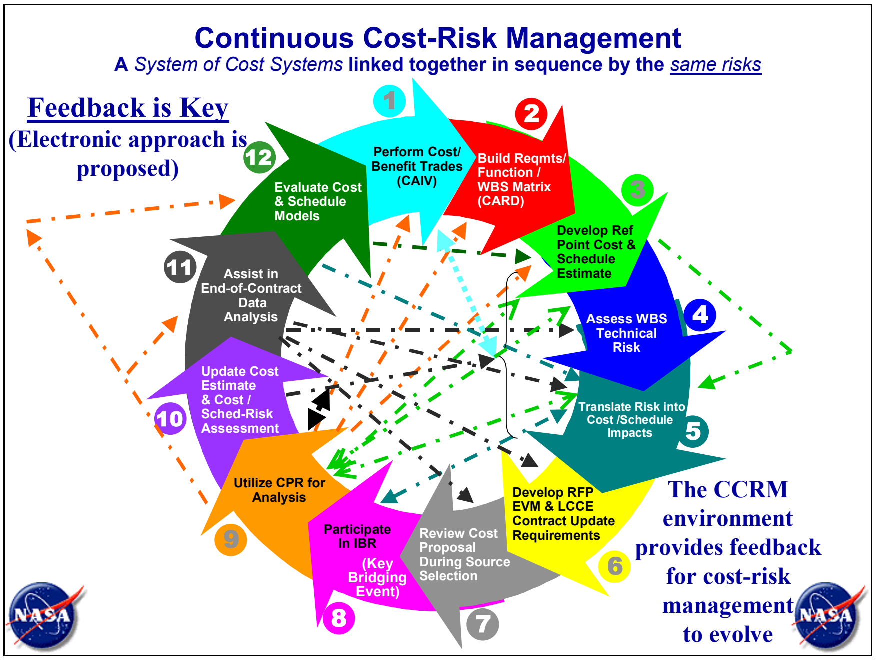

Figure 5-17

Examples of feedback between CCRM steps:

- Cost/performance trades inform RPE, tech risk, and tech risk-to-cost impact steps;
- CPR step may require a cost/performance trade, which may prompt an update to CADRe due to requirement or performance level changes, which may require an adjustment to the basic RPE;
- Cost estimator gets feedback from end-of-contract CPR cost data to update his model for improved future estimates;
- Cost estimator needs latest information on risk of a WBS element she estimated 9 months ago (for example) and contacts the CPR analyst monitoring the cost performance of that WBS element on an ongoing contract. The CPR analyst, who has electronic access to the contractor's EVM system's work package that has that high risk WBS element in it, gives the cost estimator electronic access to view current cost performance of that WBS element giving the cost estimator new insight on its risk for translation into cost impact.
- Insight for translating risk into cost impacts also comes from step 11 (technical risk-driven and external programmatic-driven risk) and 12, final end-of-contract actual cost CPR data on cost-risk performance of high and medium risk WBS elements;
- Step 11, end-of-contract technical risk-driven and external programmatic-driven risk, informs the team developing the narratives for Data Requirements for upcoming RFP solicitation documents;
- Step 11, end-of-contract technical risk-driven and external programmatic-driven risk, informs the team reviewing the bidder cost proposals for bidder past performance credibility relative to cost proposal claims;

- Step 5, translation of risk into cost impacts informs Step 8, IBR visit, by the ability to present to contractor control account managers the cost-risks identified previously in the cost estimation step by government team for validating contractor acknowledgement of responsibility to manage those cost-risks;
- Step 5 informs Steps 11 & 12 with cost performance cost-risk WBS element data, technical risk-driven and external programmatic-driven cost growth causes which can be used to create calibration factors for use during source selection;
- Step 9, CPR analysis, can also be useful to cost estimators updating their cost models in step 12;
- Step 10, updates to Reference Point Estimate and cost-risk, informs Steps 3, 4, & 5 with an updated cost and cost-risk assessment;
- Step 10 also informs the CPR Format 5 since any changes to initial cost-risks tracked in EVM system will be identified on Format 5. These changes could represent an elimination of tracking of some medium or high risk WBS element due to successfully meeting the risk challenges and/or adding a new medium or high risk WBS element for special tracking due to unexpected poor performance discovered during the effort.

Implementation Challenge: Implementing CCRM Optimality

Implementation of Continuous Cost-Risk Management throughout the NASA project and program management discipline will not happen by osmosis. A proven strategy of injecting new modes of organizational behavior is the benchmarking approach. This approach is suited to the implementation challenge of what I would term ‘achieving CCRM optimality’.

The proposal at the present time within NASA project management is to identify exactly where each project management team is relative to optimal implementation of CCRM. The first step needed is to develop a set of criteria against which each project management team can be objectively measured that indicates how well it is implementing the step of Continuous Cost-Risk Management. In this approach, each CCRM step has a number of ‘key elements’ that, if practiced by the project management team, will indicate its level of optimal CCRM implementation for that step. If there are five key elements for a particular CCRM step, as illustrated in Figure 5-18 below, and each element is equally weighted, then a ‘score’ of 5 indicates optimal implementation of that step of CCRM. If a scale of 1 to 5 is used for all CCRM steps, 1 being lowest and 5 being highest, then an average of all scores for all 12 CCRM steps would give a measure of how close to optimal a particular project management team is in implementing Continuous Cost-Risk Management. An acronym might be useful at this point to designate a quick way to relatively place a project management team on such a scale such as “CCRM 4”, indicating that over all 12 CCRM steps that team received an average score of “4” out of 5 possible. A project management team with a score of “4” may well represent the best project management team at NASA and hence would become the benchmark for all other teams to strive to meet or beat.

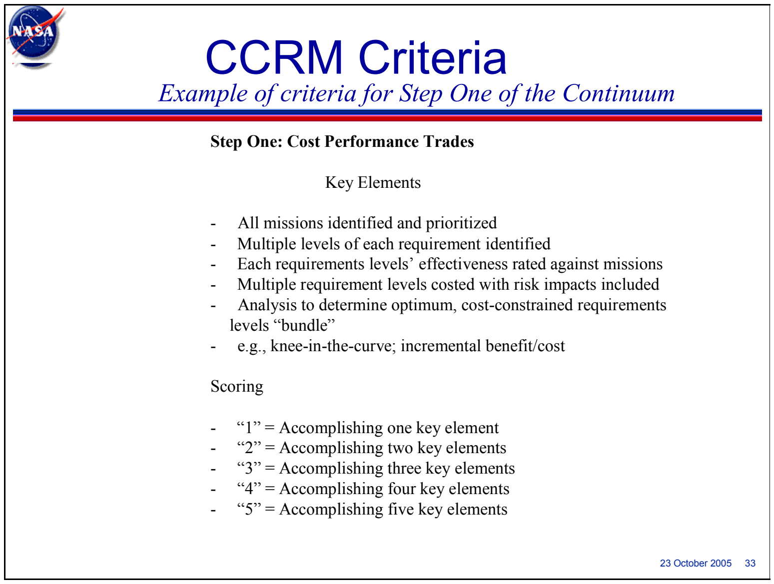

Figure 5-18

An obvious question arises as to who will have the authority to rate the teams? NASA is looking at having a knowledgeable entity with the requisite authority such as the Independent Program Assessment (IPA) review team, the Non-Advocate Review team, an ad hoc 'greybeard' project management team set up by the Chief Engineer's Office to rate project management teams, or more of a self-assessment approach somehow supervised by the Chief Engineer's Office.

The underlying hypothesis for CCRM implementation is that those project offices closer to being rated at a CCRM 5 level for every CCRM step have a more likely chance to minimize the difference between final actual costs and beginning target costs.

Since the number of project management teams at NASA is quite large, a complete CCRM rating of all these teams is probably impractical. The target project management teams NASA is considering for CCRM ratings are those with the responsibility for new development projects and programs. Priority will be given to those teams whose projects have unusually large cost targets, are highly visible and/or have a high degree of risk. In accomplishing the CCRM ratings, HQs Cost Analysis Division, Chief Engineer, Mission Directorates, IPAO and Center SMOs will work with projects/programs to educate, rate, and strive over time for project management achievement of CCRM optimality (i.e., CCRM "5").

To further enhance CCRM implementation, HQs Cost Analysis Division is working to develop an electronically based collaborative networking environment to facilitate interaction between personnel involved in implementing CCRM steps. A system such as this will accelerate CCRM education for ultimate CCRM level-5 achievement. It can also be viewed as part of OMB and Bush administration's R&D initiative for improving networking and IT R&D.

Summary

The need for a more successful approach to managing NASA programs and projects has been recognized for some time. Updating the NPD/NPR 7120.5 is the mechanism to address the policy changes necessary to achieve such success. Figure 5-19 below, taken from "The Success Triangle of Cost, Schedule, and Performance: A Blueprint for Development of Large-Scale Systems in an Increasingly Complex Environment"[5], has cost-growth areas addressed by Continuous Cost-Risk Management identified. The point of Fig. 19 is to show that CCRM is designed to identify, monitor and measure the behavior of cost-risk in the very areas pointed out by the Booz, Allen, Hamilton (BAH) study to be driving 70% of space cost growth. This chart is not meant to suggest that if CCRM were applied there would be a 70% reduction in space cost growth. It should be interpreted, as that if CCRM were applied there would be logical expectations, due to focused attention on the risks and cost-risks, that a reduction in space cost growth to some degree in the areas identified can be achieved.

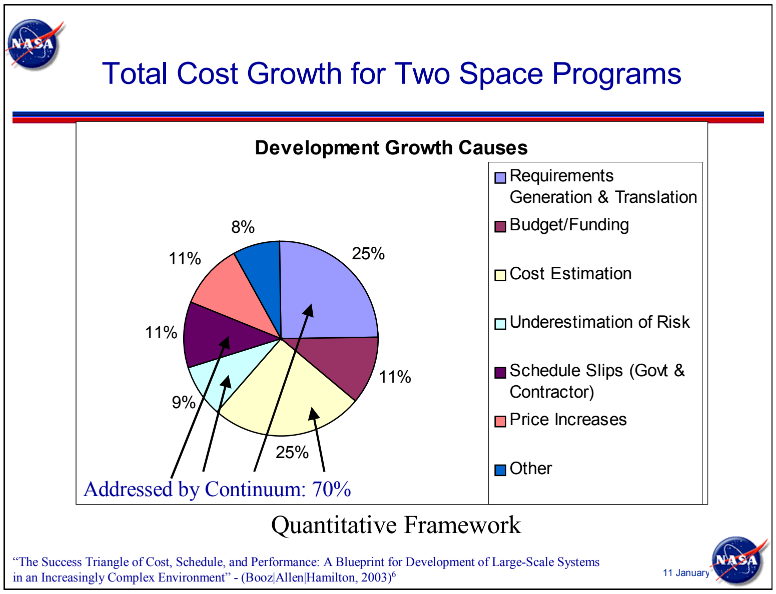

Figure 5-19

References

[1] Buschman, Sherry, "NASA Program and Project Management Processes and Responsibilities, NPR: 7120.5(C) ", 10 April 2003.

[2] Graham, David R., "Preparing, Developing and Applying Cost-Risk Feedback", Presented at The Aerospace Corporation Risk Management Symposium, May 2003.

[3] White, Frank, "The Overview Effect": Space Exploration and Human Evolution, Houghton Mifflin, 1987.

[4] "The Success Triangle of Cost, Schedule and Performance: A Blueprint for Development of Large-Scale Systems in an Increasingly Complex Environment", Booz/Allen/Hamilton, 2003.

6. Risk Analysis of a Multi-Spacecraft Satellite System

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General Dynamics, Spectrum Astro

Introduction

Realistic estimates of costs and program resources are imperative before Government decision makers approve funding for satellite programs. The programs under consideration are affected by a variety of risks. When developing cost estimates of such major cost expenditure projects, a contractor is required to quantify the effects of these risks on the project's cost and on the implementation of measures to manage and mitigate the results of these risks. Not only is risk analysis required for Government funding decisions[8], but it also provides valuable information to program managers in terms of highlighting elements that are cost sensitive and need to be monitored by management. Increasingly a company's competitive position relies on its ability to recommend the most efficient system meeting the customer's budget with acceptable risk.

Purpose

This section presents a summary of a specific approach to risk management as it relates to cost, cost risk analysis methodology, and sample cost risk results as calculated for a long-term spacecraft and ground engineering, production, replenishment, and operations and support program. During a planning phase, tradeoffs between alternative acquisition and technical strategies, for a given set of requirements, focus on obtaining the proper balance between technical, schedule, and cost program objectives. Figure 6-1 shows how cost risk analysis is part of both the risk management and the cost analysis process. Our goal is to explain a cost risk analysis methodology used to produce realistic estimates of costs and program resources for Government decision makers. The first step uses the risk management process results, which identifies and assesses potential performance, cost, and schedule risk events. The second step defines and measures sources of uncertainties to determine the cost variance. The third step quantifies the potential cost impacts from the various potential risk areas. The fourth and final step interprets and analyzes the cost data resulting from our cost risk model.

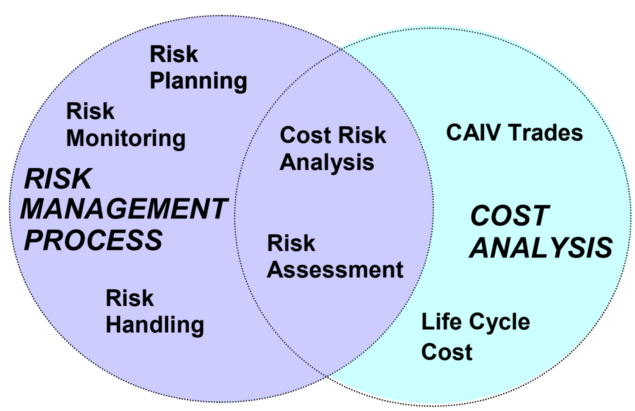

Figure 6-1 – Cost Risk Analysis Interaction With the Risk Management Process

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8 "Cost-Risk Analysis: A Tutorial", presented by Dr Stephen A Book, The Aerospace Corporation, June 2, 1997

To quantify the potential cost impacts of risk we employ Crystal Ball[9], a commercial software tool. Crystal Ball performs Monte Carlo risk analysis simulations on cost elements (cells in an Excel spreadsheet) defined as uncertain assumptions. In addition, this cost risk methodology quantifies learning curve cost risk by performing a Monte Carlo simulation on learning curve slopes (percentages). The Excel spreadsheet risk tool analyzes a large number of Nonrecurring, Theoretical First Unit (TFU), and Operations and Support (O&S) Work Breakdown Structure (WBS) elements. Separate learning curve assumptions in the cost risk model are applied to level of effort (LOE), bus, and payload TFU costs. The results of the TFU costs multiplied by a learning curve factor for multiple units, give the total spacecraft recurring production costs for the architecture. The cost risk model produces the total program's cost risk from forecasted results for nonrecurring, recurring, and operations and support WBS elements.

Risk Management

The main elements in risk management, as shown in Figure 6-2, include risk planning, assessment, handling, and monitoring[10]. One of the main goals of this approach is to fully integrate the risk management process with the cost risk analysis in order to maintain consistency in the evaluations of risk. Also this may improve program risk management by focusing on cost risk drivers identified in cost risk analysis.

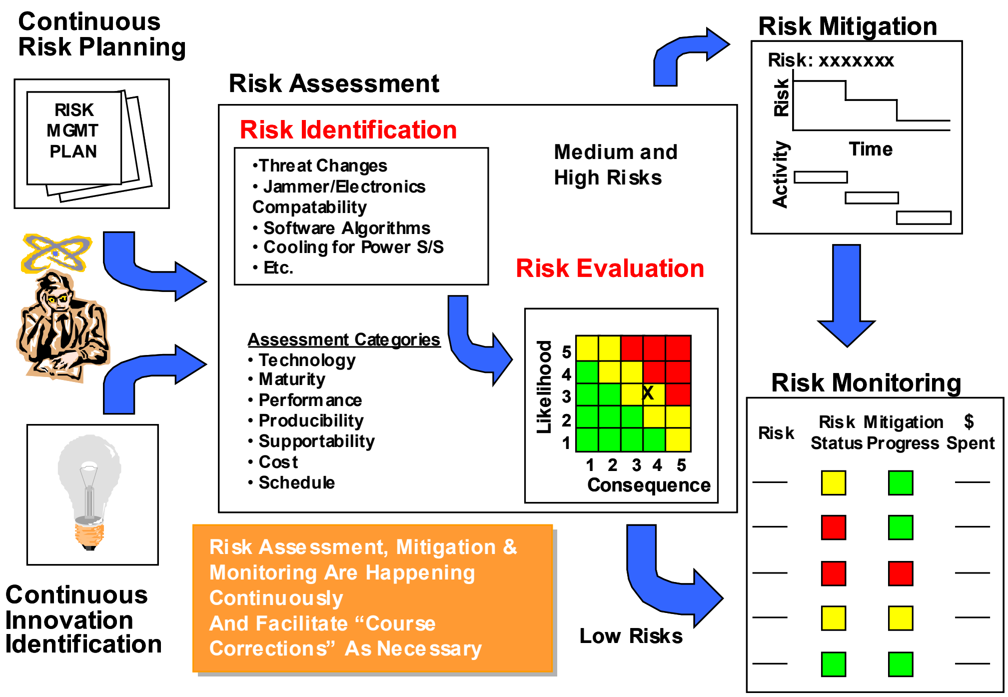


Figure 6-2 Risk and Innovation Planning is Iterative and Consists of Assessment, Mitigation, and Monitoring

The objective of the risk assessment function is to first identify and analyze each program area and critical technical process risk and the work breakdown structure elements that they affect. Table 6-1 shows a partial list of the high risks in a notional program (across the top), and corresponding WBS elements that are affected by the risk named.

9 Crystal Ball 2000 User Manual, Decisioneering, Inc., Denver, Colorado.
10 AFMC Pamphlet 63-101 Acquisition Risk Management July 9, 1997

Table 6-1 Risk Cross-Reference Matrix

WBS ID Number	WBS Name	Correlation to Top Risks	SV IAT&C	PL IAT&C	PL Thermal	PL LOS System	SV and PL Processing	PL Focal Plane Assembly	Ground Software	Ground IA&T	Survivability	System Certification	System IA&T	
			70	113	24	75	60	9	27	28	41	5	19	
222110	Focal Plane Electronics/Cable							X NR						
222120	Focal Plane Design Integ							X NR						
22221121	Pointing and Control Structure					X NR								
22221124	Pointing and Control Flex					X NR								
22221126	Pointing and Control Design Integ					X NR								
22222111	Processor Structure						X NR TFU							
22222112	Processor Chips						X NR TFU							
22222115	Processor Substrate						X NR TFU							
22222117	Processor Design Integ						X NR							
222310	Heat Pipe Assy				X NR TFU									
222380	Transport Rod				X NR TFU									
2223A0	Transverse Assys				X NR TFU									
2223C0	Thermal Design Integ				X NR									
2223D0	Thermal I&T				X NR TFU									
222700	Payload Software						X NR							
23210	Structure Design and Analysis			X NR TFU										

Secondly, the objective of the risk assessment function is to rank and score each WBS element based on specific criteria developed by the Risk Integrated Process Team (RIPT). A detailed list of tasks orchestrated by the RIPT is provided below:

Risk Planning and Identification Tasks:

1. Define WBS elements to assess.
2. Identify responsible person for each WBS element.
3. Describe architecture based on requirements and design.
4. Define risk assessment criteria and initial risk list categories.
5. Train assigned WBS personnel on risk procedures.

Risk Assessment Tasks:

1. Assess risk for each WBS.
2. Review assessments for architecture consistency and currency of technology base.
3. Map WBS level risks to risk score list.
4. Assign high, medium, low to risk score list.
5. Provide risk score list inputs to cost team.
6. Provide distribution symmetry inputs (cost distribution skew values) to cost team.
7. Provide risk correlation factors to cost team.
8. Review/approve risk list and status.

Risk management is an iterative process. The risk team evaluates the initial risk assessments as soon as the System Architecture and Design Integrated Process Team (AIPT) defines the architecture concept. The risk team is comprised of contractor and government engineers and technical experts. Risk assessment is made continuously throughout the life of the long-term spacecraft and ground engineering, production, replenishment, and operations and support program.

In this notional multi-spacecraft satellite system, the traditional three risk categories: performance, cost and schedule are assessed for risk events. In addition, the performance category is further divided into: technology, maturity, performance, producibility, and supportability. This gives us seven major categories to assess program uncertainty. Technology and Maturity is further split into two parts, hardware and software for scoring. The RIPT evaluates each risk area, as applicable, against the nine risk categories to determine an overall cost risk score used initially by the RIPT to identify and monitor risk (see Appendix A[11] for criteria definitions). A five-increment "low to high" scale is used to discriminate among relative levels of risk or uncertainty for each category as shown in Table 6-2. A consequence, should the cost risk event occur, for each risk area is also scored by the RIPT. The maximum probability column is the highest score from any of the uncertainty categories. This score is added together with the consequence score to give the consequence and probability column score. The maximum probability/ consequence score is used to determine the risk level ranking of low, medium or high based on the probability/consequence matrix shown in Figure 6-3.

These risk assessments serve as an input in establishing the bounds around the point estimates for the cost risk analysis[12].

Table 6-2 RIPT Risk Assessments

Risk ID	Risk Title	Date	HW Technology	SW Technology	HW Maturity	SW Maturity	Performance	Producibility	Supportability	Cost	Schedule	Consequence	Max Prob	Cons & Prob	Risk Rating
70	SV IAT&C	4/02	3	5	3	5	5	5	3	5	5	5	5	10	H
113	PL IAT&C	1/03	4	4	4	4	5	4	4	4	5	5	5	10	H
24	PL Thermal	2/03	3		5		5	4		3	3	4	5	9	H
75	PL LOS System	3/03	5		5		5	5		5	5	4	5	9	H
60	SV and PL Processing	12/02	3	3	4	3	4	4	3	3	3	4	4	8	H
9	PL Focal Plane Assembly	4/03		4		4	4	4	3	4	4	4	4	8	H
27	Ground Software	8/02	2	2	4	4	4	3	4	2	3	4	4	8	H
28	Producibility of TWTs	4/03	2	3	2	3	3	3		3	3	3	3	6	M
41	System Integration	4/03	2	2	2	2	2	2	2	2	2	2	2	4	L

[11] A set of risk factors were defined the GPALS Risk Management Procedures Manual, GE/Aerospace, dated 6 April 1992, and further refined in the LMMS document Systems and Specialty Engineering Organization Guide to Risk Assessment, LMMS-P421268, dated 2 March 1995.
[12] The Cost-Risk Identification & Management System (CRIMS) Developed by David R. Graham (SMC/FMC), and Jason Dechoretz (MCR), Space and Missile System Center, September 1994.

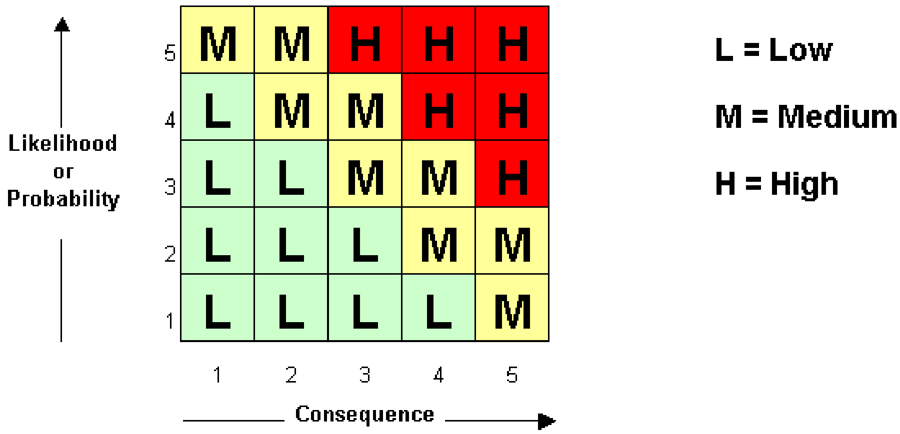


Figure 6-3 RIPT Scoring of Risks Based on Likelihood and Consequences

To summarize, the RIPT scoring process involves the following steps:

1. The risk is described. The most likely program impact is identified that could be attributed to this risk.
2. The impact is quantified, such as, growth of pounds, watts, dollars, or slip of so many months.
3. The risk factor for each of the risk categories is estimated using the criteria tables in Appendix A. If a category is not applicable, no factor for that category is entered. If one or more categories apply, the highest score from the riskiest category is chosen.
4. The factors for each applicable category are documented and a rationale for the risk factors chosen is included.
5. The consequence factor for the risk is determined using the tables in Appendix A.
6. The maximum probability of occurrence factor score and the consequence factor score are applied to the 5x5 matrix to determine the level of risk — high, medium or low.
7. The Responsible Engineer Authorities (REAs) generate Risk Mitigation Plans for all identified medium and high risks.
8. The REAs also generate Contingency Plans for all risk elements should the mitigation activities fail to perform the requisite risk reduction in the allotted schedule and budget assigned to the risk mitigation activity.

Risk Mitigation Plans

Risk mitigation is the process that identifies, evaluates, selects and implements activities that reduce risk to acceptable levels given program constraints and objectives. As the risk process goes through iterations, the cost risk analysis provides Program Management with cost risk drivers for the program. This information is used in making decisions as to which performance, technical and schedule risks should be mitigated and the level of resources committed.

Risk monitoring activities assess the progress made toward risk reduction by the continual tracking of risk mitigation plans throughout the development cycle to ensure effective mitigation. The effectiveness of risk mitigation activities is to reduce the risk level over time. Quite often these risk reductions coincide with major program events, System Readiness Review (SRR), System Design Review (SDR), Preliminary Design Review (PDR), Critical Design Review (CDR), or demonstration events not at program milestones. As risk levels are reduced, so are the cost uncertainties. Figure 6-4 shows risk reductions for seven risk categories over time, spanning SRR through CDR. Risk is re-scored approximately every four months to provide management with up-to-date information following the risk reduction profiles.

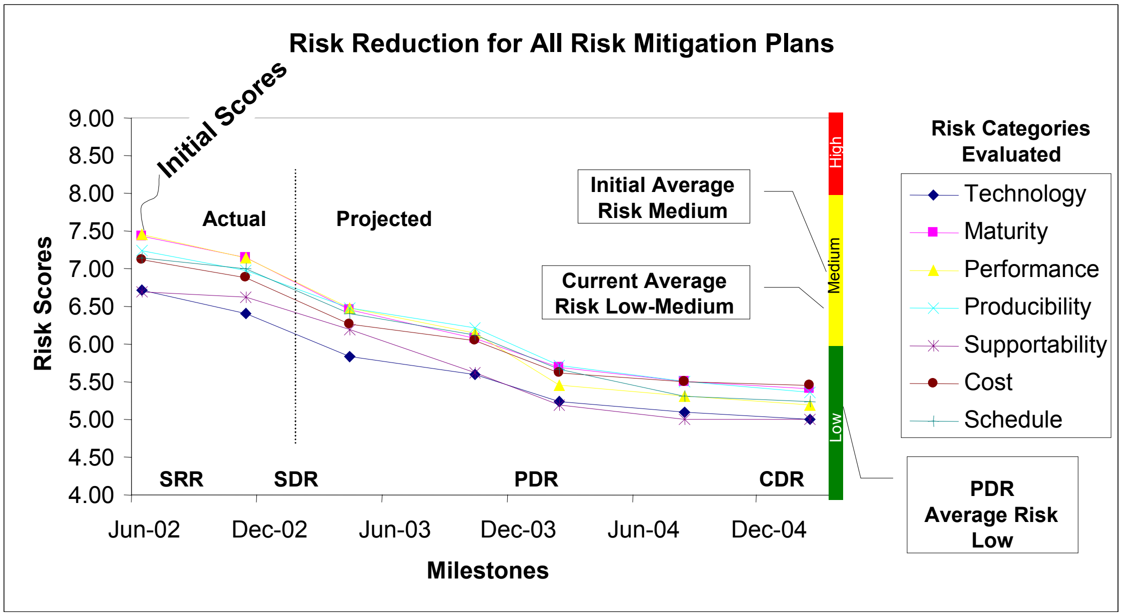


Figure 6-4 Risk Reduces at Each Milestone

Cost Risk Analysis Methodology

In our cost risk model we have programmed the software to perform Monte Carlo simulations using Crystal Ball 2000 for Windows (Version 5.0) on WBS cost elements and learning curve (percentages) defined as being uncertain, to quantify the potential cost impacts of risk on our multi-spacecraft satellite program Life Cycle Cost (LCC) estimate. This process contains the following steps:

1. Identify the most probable LCC point estimate.
2. Identify the most probable learning curve percentages for spacecraft (or bus), payload, LOE, and Orbital Insertion System (OIS) elements.
3. Identify probability distribution (Triangular or Uniform) for most probable costs and learning curve uncertainties.
4. Identify levels of uncertainty by evaluating the risk scores for the most probable costs. Pick learning curve uncertainties based on historical production basis, etc.
5. Select the distribution symmetry (Skew Left, Symmetrical, or Skew Right) based on confidence in the point estimate.
6. Establish the range of the distribution from the look-up table for most probable costs and learning curve uncertainties.
7. Identify the correlation between WBS elements for costs.
8. Define assumptions and forecasts in Crystal Ball for costs and learning curves.
9. Load the WBS element correlation matrix.
10. Perform Monte Carlo simulation in Crystal Ball (10,000 iterations).

Cost Analysis Assessment

The scores determined in the risk assessment process are transferred and used in the cost risk assessment process. This ensures that evaluations used in the risk management process and cost risk analysis are consistent. The cost assessment evaluates the cost risks from the same nine risk categories although technology and maturity hardware and software scores are now combined using the highest score of the two. How these cost categories are split between nonrecurring and recurring costs is shown below:

a. Hardware and software technology – Nonrecurring.
b. Hardware and software maturity – Nonrecurring.
c. Performance – Nonrecurring.
d. Producibility – Recurring (TFU and Operations and Support).
e. Supportability – Recurring (TFU and Operations and Support).
f. Cost – Nonrecurring and Recurring (TFU and Operations and Support).
g. Schedule – Nonrecurring and Recurring (TFU and Operations and Support).

Nonrecurring costs include software, qualification model, and pre-production space vehicles cost categories associated with the first launch. They also include nonrecurring O&S costs; for example, systems engineering/program management, systems test and development, data, peculiar and common support equipment, ground spares, depot maintenance, training, flight support, and transportation and storage.

The recurring factors are applied to the first production unit's cost. The recurring risk cost factors are also applied to the non-space and O&S related (not including nonrecurring) costs. This includes the dispenser, ground, systems engineering/program management, systems test and evaluation, data, depot maintenance equipment and data, training, flight support operations and service, and transportation and storage costs.

As a result of our process, the cost evaluations of risk are consistent with the technical evaluations used to rank the program risk list. The risk factors from each applicable category are averaged to obtain a single number to represent the cost risk associated with each WBS element. This averaged probability cost risk score is shown in Table 6-3 in the column labeled "Risk Score."

Table 6-3 also shows the TFU cost risk assessment by WBS. This is a partial listing of TFU cost risk assessments; scores are assigned to each nonrecurring, recurring and operations and support WBS element.

In addition to the risk level factors, a distribution symmetry input for each low-level WBS element is also required. Selection of the distribution symmetry is based on confidence in the point estimate. The individual analyst who provides the initial point estimate cost, and the RIPT, reviews the risk levels and distribution symmetry inputs prior to generating the cost impacts with Crystal Ball. This ensures that cost evaluations are consistent with the risk inherent in the estimating methodologies used to estimate the individual WBS element costs. If there are any inconsistencies, the RIPT lead will consult with the original engineer to clarify the underlying assumptions and collaborate to make changes as necessary.

Table 6-3 TFU Cost Risk Assessments

WBS #	WBS Element Description	TFU (Thru G&A)	LC Slope	Producibility Risk	Supportability Risk	Cost Risk	Schedule Risk	Risk Score	Overall Risk Level
00000	Multi-Spacecraft Satellite Program	$ 97.7 M							
10000	Space Segment	$ 90.4 M							
20000	Space Vehicle	$ 90.4 M							
21000	SV Systems Engrg/Prog Mgmt	$ 2.3 M							
21100	SV Systems Engineering	$ .9 M	0.980	3.0	3.0	3.0	3.0	3.0	M
21200	Space Vehicle Prog Mgmt	$ 1.4 M	0.980	3.0	2.0	2.0	2.0	2.3	ML
22000	Payload	$ 48.9 M							
22100	Payload Prog Mgmt/Sys Engrg	$ 25.7 M							
22110	Payload Systems Engineering	$ 12.5 M	0.980	3.0	3.0	3.0	3.0	3.0	M
22120	Payload Program Management	$ 13.3 M	0.980	3.0	2.0	2.0	2.0	2.3	ML
22200	Payload Sensors	$ 23.1 M							
222100	Navigation Sensor	$ 2.8 M							
222110	Focal Plane Electronics/Cable	$ .9 M	0.930	1.0	1.0	1.0	1.0	1.0	VL
222120	Focal Plane Design Integ	$ 0 M							
222130	Power Supply	$ .4 M							
222131	Power Supply Cables	$ .3 M	0.930	2.0	1.0	1.0	1.0	1.3	L
222132	Power Supply Structure	$ .0 M	0.930	2.0	1.0	1.0	1.0	1.3	L
222133	Power Supply I&T	$ .1 M	0.930	3.0	2.0	2.0	2.0	2.3	ML

The averaged probability risk score and the distribution symmetry factor are then mapped into a "Cost Risk Factors Look-up Table," (see Table 6-4) to derive a low and high cost risk factor. The point cost estimate is multiplied by the factors obtained from the cost risk factor table to calculate the end points of a distribution for each detailed WBS element.

Table 6-4 Risk Levels Determined by Average Risk Factors and Distribution Symmetry

Average Probability Risk Factor Value (Pr)	Risk Levels	Cost Risk Factors: Skewed Left SL Low	Skewed Left SL High	Symmetric Low	Symmetric High	Skewed Right SR Low	Skewed Right SR High
1.0 < Pr ≤ 1.2	VL	0.96	1.02	0.97	1.03	0.98	1.12
1.2 < Pr ≤ 2.0	L	0.93	1.03	0.95	1.05	0.97	1.21
2.0 < Pr ≤ 2.5	ML	0.90	1.04	0.93	1.07	0.96	1.30
2.5 < Pr ≤ 3.5	M	0.85	1.05	0.90	1.10	0.95	1.45
3.5 < Pr ≤ 4.0	MH	0.80	1.10	0.85	1.15	0.90	1.60
4.0 < Pr ≤ 4.8	H	.070	1.10	0.80	1.20	0.90	1.90
4.8 < Pr ≤ 5.0	VH	0.50	1.10	0.70	1.30	0.90	2.50

Once we have distribution symmetry and average probability risk factors, the next step in our cost risk analysis is to update our assumption and forecast definitions in our Crystal Ball cost risk model. The probability distributions and ranges are the assumptions for the non-summing level WBS cost elements. Forecasts are the summations of the lower level assumptions. Table 6-5 illustrates how assumptions relate to forecasts.

Table 6-5 Sample Assumptions and Forecasts Bound the Cost Risk

WBS NO.	WBS ELEMENT DESCRIPTION	NR (Thru G&A)	Risk Level	Distribution Symmetry	Lookup Variable	Low	High	Distribution End Points LOW	Distribution End Points HIGH	Crystal Ball Analysis	Cell Type (F & a)
00000	Multi-Spacecraft Satellite Prog	$ 1,192.3 M			-			$ 1,086.0 M	$ 1,473.8 M	$ 1,192.3 M	Forecast
10000	Space Segment	$ 695.3 M			-			$ 635.9 M	$ 875.6 M	$ 695.3 M	sum
20000	Space Vehicle	$ 681.2 M			-			$ 622.5 M	$ 860.8 M	$ 681.2 M	sum
21000	SV Systems Engrg/Prog Mgmt	$ 11.0 M			-			$ 10.1 M	$ 12.0 M	$ 11.0 M	sum
21100	SV Systems Engineering	$ 4.8 M	ML	S	ML	0.930	1.070	$ 4.5 M	$ 5.2 M	$ 4.8 M	Assumption
21200	Space Vehicle Prog Mgmt	$ 6.2 M	M	S	M	0.900	1.100	$ 5.6 M	$ 6.8 M	$ 6.2 M	Assumption
22000	Payload	$ 412.2 M			-			$ 376.1 M	$ 549.7 M	$ 412.2 M	sum
22100	Payload Prog Mgmt/Sys Engrg	$ 137.6 M			-			$ 123.8 M	$ 151.4 M	$ 137.6 M	sum
22110	Payload Systems Engineering	$ 70.4 M	M	S	M	0.900	1.100	$ 63.3 M	$ 77.4 M	$ 70.4 M	Assumption
22120	Payload Program Management	$ 67.3 M	M	S	M	0.900	1.100	$ 60.5 M	$ 74.0 M	$ 67.3 M	Assumption
22200	Payload Sensors	$ 274.6 M			-			$ 252.2 M	$ 398.3 M	$ 274.6 M	sum
222100	Navigation Sensor	$ 18.5 M			-			$ 17.0 M	$ 21.8 M	$ 18.5 M	sum
222110	Focal Plane Electronics/Cable	$ 4.0 M	MH	S	MH	0.850	1.150	$ 3.4 M	$ 4.6 M	$ 4.0 M	Assumption
222120	Focal Plane Design Integ	$ 1.9 M	MH	S	MH	0.850	1.150	$ 1.6 M	$ 2.2 M	$ 1.9 M	Assumption
222130	Power Supply	$ 3.5 M						$ 3.3 M	$ 3.7 M	$ 3.5 M	sum
222131	Power Supply Cables	$ 1.8 M	L	S	L	0.950	1.050	$ 1.7 M	$ 1.9 M	$ 1.8 M	Assumption
222132	Power Supply Structure	$ 1.0 M	VL	S	VL	0.970	1.030	$ 1.0 M	$ 1.0 M	$ 1.0 M	Assumption
222133	Power Supply I&T	$ .7 M	ML	S	ML	0.930	1.070	$ .7 M	$ .8 M	$ .7 M	Assumption
222140	Platform Assembly	$ 7.3 M						$ 7.0 M	$ 9.1 M	$ 7.3 M	sum
222141	Camera	$ 6.8 M						$ 6.5 M	$ 8.5 M	$ 6.8 M	sum
2221411	Telescope	$ .7 M	ML	S	ML	0.930	1.070	$ .7 M	$ .8 M	$ .7 M	Assumption

WBS Mapping and Correlation Coefficients

The correlation between WBS elements is based on a dependency of the statistical parameters associated with each element and provides a more realistic calculation for the variance. For example, cost distributions associated with the solar array and battery are dependent on other WBS element power needs and associated cost distributions. Design and analysis cost distributions are dependent on individual hardware and software configuration items. Engineering and technical experts take the high-risk drivers and assess them with the WBS elements that they affect. If they agree there is a correlation between the elements, they determine the correlation coefficient. The high-risk elements previously shown in Table 6-1, Risk Area Cross-Reference Matrix, shows a partial list of which cost element distributions are correlated. Table 6-6 contains the risk correlation mapping and correlation coefficients by WBS element. Crystal Ball, which uses a rank correlation to correlate assumptions, uses the correlation coefficient to align the dependent probability distributions during the simulation. Correlation coefficients range from –1 to +1 providing three types of correlation: negative, zero, and positive. Correlating WBS element cost distributions is a challenging task because correlation works best when working with single discrete variables and their probability distributions. Once correlation coefficients are determined, standard Crystal Ball features are used in the simulation to analyze how WBS elements influence other elements.

Table 6-6 WBS to Risk Mapping

Risk #	Risk Description	WBS ID Number	WBS Description	Correlation Top Risks	Correlation Factor
#9	PL Focal Plane Assy				
		222110	Focal Plane Electronics/Cable	NR	0.2
		222120	Focal Plane Design Integ	NR	0.3
#75	PL LOS System				
		22221121	Pointing and Control Structure	NR	0.1
		22221125	Pointing and Control Substrate	NR	0.2
		22221126	Pointing and Control Design Integ	NR	0.5
#60	SV and PL Processing				
		22222111	Processor Structure	NR TFU	0.2
		22222112	Processor Chips	NR TFU	0.5
		22222115	Processor Substrate	NR TFU	0.3
		22222116	Processor Flex	NR TFU	0.3
		22222117	Processor Design Integ	NR	0.2
		222700	Payload Software	NR	0.5
		23A00	Spacecraft Integ, Assy/Test/Ckout	NR	0.2
#24	PL Thermal				
		222310	Heat Pipe Assy	NR TFU	0.2
		222320	Heat Pipe Electronics	NR TFU	0.5
		222330	Heat Pipe Distribution Box	NR TFU	0.3
		222370	Transport Heat Pipe	NR TFU	0.2
		222380	Transport Rod	NR TFU	0.1
		2223A0	Transverse Assys	NR TFU	0.1
		2223C0	Thermal Design Integ	NR	0.4
		2223D0	Thermal I&T	NR TFU	0.5

Detailed Cost Risk Distributions and Methodology Used to Establish Minimum and Maximum Risk Factors for Distribution Functions

From Table 6-4, a low and high factor is obtained. The model uses a Point Estimate (PE) of 1 for the “most likely” or mode occurrence. The minimum and maximum cost factors offset from 1. The low and high factors are multiplied by the point estimate (or mode) cost to calculate the low and high cost summations as shown in Table 6-7.

Although not shown, nonrecurring, recurring, and operations and support cost distributions are calculated for each WBS element in this same manner.

Table 6-7 TFU Cost Distributions

		Theoretical First Unit							
		TFU	TFU	Distribution	Calculated			LOW	HIGH
WBS #	WBS Element Description	(Thru G&A)	Yes/No	Symmetry	Low	High	Mean	Summation	Summation
00000	Multi-Spacecraft Satellite Prog	$ 185.3 M							
10000	Space Segment	$ 171.6 M							
20000	Space Vehicle	$ 171.6 M							
21000	SV Sys Engrg/Prog Mgmt	$ 1.6 M						$ 1.5 M	$ 1.7 M
21100	SV Systems Engineering	$ .8 M	Yes	S	0.900	1.100	1.000	$ .7 M	$ .8 M
21200	Space Vehicle Prog Mgmt	$ .9 M	Yes	S	0.930	1.070	1.000	$ .8 M	$ .9 M
22000	Payload	$ 107.5 M							
22100	Payload Prog Mgmt/Sys Engrg	$ 60.0 M						$ 54.9 M	$ 65.1 M
22110	Payload Systems Engineering	$ 30.0 M	Yes	S	0.900	1.100	1.000	$ 27.0 M	$ 33.0 M
22120	Payload Program Management	$ 30.0 M	Yes	S	0.930	1.070	1.000	$ 27.9 M	$ 32.1 M
22200	Payload Sensors	$ 47.5 M							
222100	Navigation Sensor	$ 5.5 M							
222110	Focal Plane Electronics/Cable	$ 1.8 M	Yes	S	0.970	1.030	1.000	$ 1.7 M	$ 1.8 M
222120	Focal Plane Ele/Cab Design Integ		No						
222130	Power Supply	$ .8 M						$ .8 M	$ .8 M
222131	Power Supply Cables	$ .6 M	Yes	S	0.950	1.050	1.000	$ .6 M	$ .6 M
222132	Power Supply Structure	$ .1 M	Yes	S	0.950	1.050	1.000	$ .1 M	$ .1 M
222133	Power Supply I&T	$ .1 M	Yes	S	0.930	1.070	1.000	$ .1 M	$ .1 M
222140	Platform Assembly	$ 2.5 M							
222141	Camera	$ 2.4 M							
2221411	Telescope	$ .3 M	Yes	SR	0.950	1.450	1.133	$ .3 M	$ .5 M
2221412	Mirrors	$ 2.0 M						$ 1.9 M	$ 2.8 M
22214121	Mirrors Mechanisms	$ 1.5 M	Yes	SR	0.950	1.450	1.133	$ 1.5 M	$ 2.2 M
22214122	Mirrors Filter	$ .3 M	Yes	SR	0.960	1.300	1.087	$ .3 M	$ .4 M

The triangular distribution function is used most often in our risk model; the uniform distribution function is used occasionally. Three types of triangular distributions (Symmetric, Left Skewed and Right Skewed), along with seven risk levels provide 21 different triangular distribution functions available for use. How the structure of the triangular distribution function is affected by changes in risk levels is shown in Figure 6-5. As the risk goes from very low to very high, the minimum and maximum values change as the arrows indicate. For the very low risk symmetric distribution function, the minimum and maximum values tend to be very close to the PE. This is because cost estimates are based on catalog prices or vendor quotes for off-the-shelf items. As risks increase, cost PEs become less precise, as prices are based on estimates with less historical background and cost reliance is more on experience with similar systems than on actual prices. Uniform distributions behave similar to triangular distributions except the cost probability of occurrence is the same for point estimate, minimum, maximum and all points in between.

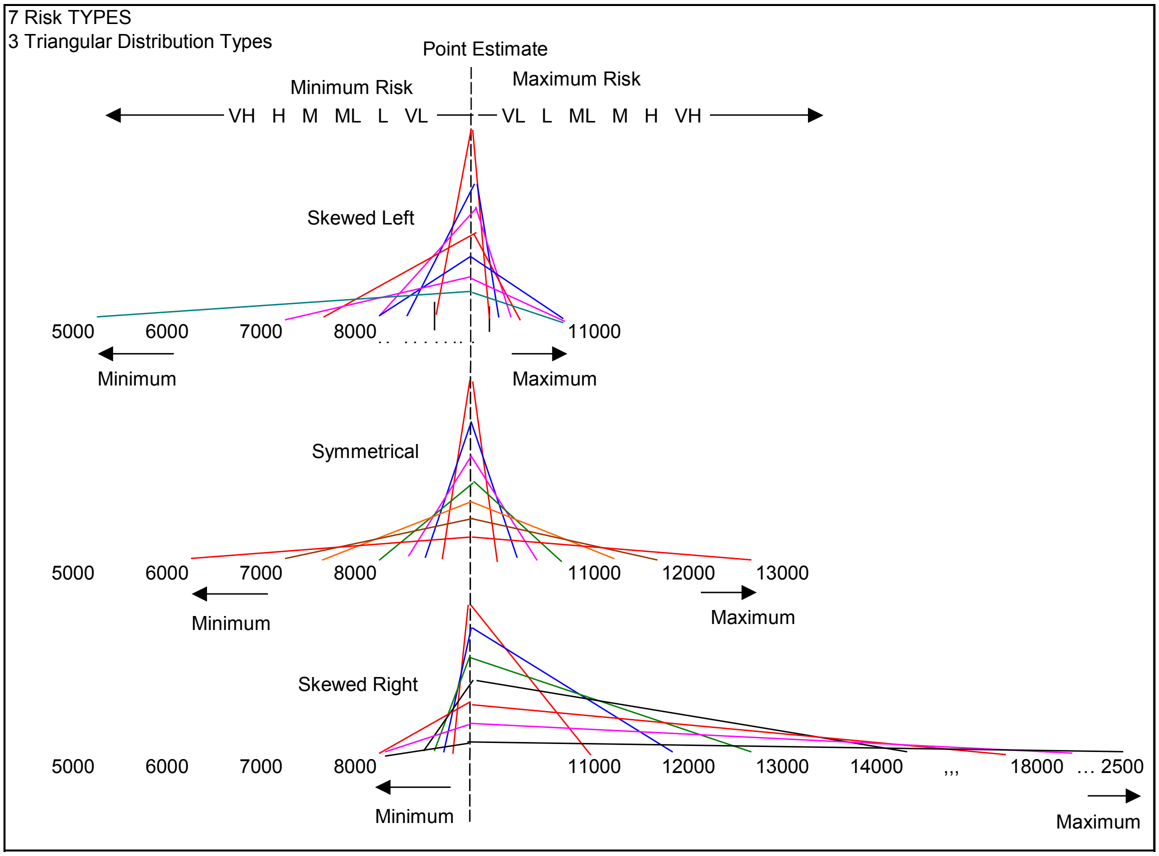


Figure 6-5 Characteristics of the Triangular Distribution Functions

Triangular distribution functions that are skewed to the left have a greater confidence that the ultimate cost is at or below the PE. For a very low risk, the skewing is only slight with the minimum relatively close to the PE. This represents an off-the-shelf item with significant cost history. As the risk level increases, the potential for greater cost reductions are possible. The development of computer processors using new technology may use the skewed left distribution at higher risk levels. While the risk level increases, the trend in electronic items like computer processors has been for the cost to decrease or for increase in capability for the same cost. Increasing buys from lower to higher quantities may also be justification for using a skewed left distribution that has a higher probability for lower cost.

The right skewed distributions have a greater confidence that the ultimate cost will be at or above the PE. As the risk level increases, the maximum value increases with a higher rate of increase as the risk transitions above moderate low. Developing new technologies for low volume components might cost several times more than expected with little pay back in low volume productions. Experience shows that as the risk level increases, the rate of the maximum increases and does not appear to be linear. In pre-EMD programs, the right skewed distributions maximum values reflect the possibility that the item/technology may have to be abandoned at some point in the program.

LCC at 50% Confidence Level

Once all the assumptions, forecasts, and correlations have been defined, a Monte Carlo simulation run is performed. We set each simulation run for a maximum of 10,000 iterations and use the Monte Carlo method to generate random values for each assumption for the costs and learning curves. During the simulation run, the assumption cells deviate up or down based on the probability distribution assigned and these deviations are collected in the forecast distribution. Each set of random numbers effectively simulates a single "what-if" scenario for each assumption. We generate a cumulative distribution for each forecast cell (the total, level one, and level two WBS cost elements) at the 20th, 50th, and 80th percentiles.

The cost risk model evaluates cost uncertainties based on a point estimate, high and low endpoints of cost distributions. The recurring TFU spacecraft and orbital insertion systems have uncertainties not only in cost, but in the learning curves too. The risk model analyzes the cost uncertainty and simultaneously analyzes the learning curve uncertainty based on a point estimate and end points of distribution of a learning curve percentage. Spacecraft and payload learning curve percentages are determined by cost team analysis through studies analyzing historical production data. The cost risk model statistically adds the nonrecurring, the total recurring spacecraft, and operation and support costs as shown in Figure 6-6.

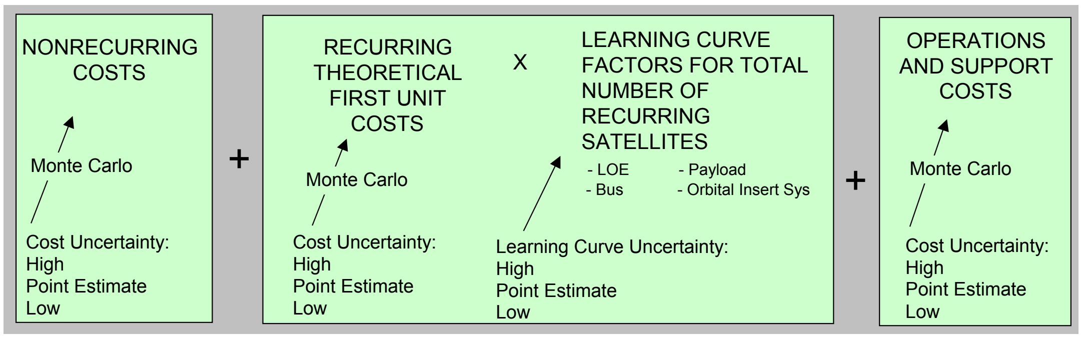


Figure 6-6 Cost Risk Model Calculation Process

The TFU cost uncertainty result is multiplied by total number of space vehicles raised by the curve factor ((log (learning curve percentage)/log (2)) +1) uncertainty. Figure 6-7 shows how the risk model is constructed to run the distributions to calculate the TFU cost.

Table 6-8, Table 6-9, and Table 6-10 contain the top-level results of our cost analysis of the nonrecurring, recurring (including operations and support), and total LCC, respectively. In addition, Crystal Ball Report provides statistical information on the cumulative distribution for each forecasted WBS element. The statistical information for the total forecast costs is shown in Figure 6-8.

	Point LC	Minimum LC	Maximum LC	CB Names	Learning Curve Slopes		b+1
LOE	98.0%	95.0%	100.0%	LC-LOE	98.0%	Assumption	0.9708537
Payload	93.0%	92.0%	97.0%	LC-Payload	93.0%	Assumption	0.8953026
Spacecraft (Bus)	90.0%	88.0%	95.0%	LC-SC	90.0%	Assumption	0.8479969
OIS	100.0%	100.0%	100.0%	LC-OIS	100.0%	Assumption	1.0000000

Learning Curves Vary due to Monte Carlo simulations based on Point , Minimum & Maximum Learning Curves

b=(LN(Learn Curve)/LN(2))+1

# of Orbital Insertion System	13
# of Space Vehicles	46

TFU								**SV 1+**
Point Est (Thru G&A)	**LC Slope**	**Distribution End Points Minimum**	**Maximum**	**Crystal Ball Names**	**Crystal Ball Analysis**	**Cell Type (F & a)**	b+1	**TFU (Thru G&A)**
$ 90.4 M	0.000	$ 83.3 M	$ 105.3 M	**T1-00000**	$ 90.4 M	**Forecast**		$ 3,020.7 M
$ 90.4 M	0.000	$ 83.3 M	$ 105.3 M	**T1-10000**	$ 90.4 M	sum		$ 3,020.7 M
$ 90.4 M	0.000	$ 83.3 M	$ 105.3 M	**T1-20000**	$ 90.4 M	sum		$ 3,020.7 M
$ 2.3 M	0.000	$ 2.1 M	$ 2.5 M	**T1-21000**	$ 2.3 M	sum		$ 93.8 M
$ .9 M	0.980	$ .8 M	$ 1.0 M	**T1-21100**	$ .9 M	Assumption	**0.971**	$ 35.9 M
$ 1.4 M	0.980	$ 1.3 M	$ 1.5 M	**T1-21200**	$ 1.4 M	Assumption	**0.971**	$ 57.9 M
$ 48.9 M	0.000	$ 45.1 M	$ 58.8 M	**T1-22000**	$ 48.9 M	sum		$ 1,771.7 M
$ 25.7 M	0.000	$ 23.6 M	$ 27.9 M	**T1-22100**	$ 25.7 M	sum		$ 1,058.6 M

Costs Vary due to Monte Carlo simulations based on Point Estimate, Minimum and Maximum Cost Estimates.

=CB analysis (column S) *((Total # SV (46) ^ b+1))

Figure 6-7 Cost Analyst's TFU Cost Calculation Process

Table 6-8 Cost Analyst's Nonrecurring Cost Risk Summary

WBS #	NONRECURRING WBS Element Description	Point Estimate (PE)	Percentile 20%	50%	80%	Variance PE Less 50%	% Diff =Var/PE
00000	Multi-Spacecraft Satellite Program	$ 1,282.8 M	$ 1,325.5 M	$ 1,343.9 M	$ 1,362.8 M	$ 61.1 M	4.8%
10000	Space Segment	$ 785.7 M	$ 811.7 M	$ 827.0 M	$ 845.9 M	$ 41.3 M	5.3%
20000	Space Vehicle	$ 771.6 M	$ 797.6 M	$ 812.8 M	$ 831.8 M	$ 41.2 M	5.3%
22000	Payload	$ 461.1 M	$ 480.7 M	$ 495.1 M	$ 513.7 M	$ 34.0 M	7.4%
23000	Spacecraft (Bus)	$ 221.5 M	$ 224.2 M	$ 227.3 M	$ 231.1 M	$ 5.7 M	2.6%
24000	Orbital Insertion System	$ 22.9 M	$ 22.5 M	$ 22.9 M	$ 23.4 M	$ .0 M	0.1%
25000	Support Equipment	$ 23.6 M	$ 24.1 M	$ 24.7 M	$ 25.5 M	$ 1.1 M	4.8%
26000	SV Integ, Ass, Test & Ckout	$ 29.2 M	$ 27.8 M	$ 29.1 M	$ 30.4 M	($ .1 M)	-0.4%
27000	Launch Vehicle	$ 14.1 M	$ 13.8 M	$ 14.1 M	$ 14.4 M	$ .0 M	0.1%
30000	Ground Segment	$ 318.6 M	$ 325.5 M	$ 333.8 M	$ 341.5 M	$ 15.2 M	4.8%
40000	System Engrg/Program Mgmt	$ 18.6 M	$ 18.6 M	$ 19.0 M	$ 19.4 M	$ .4 M	2.1%
50000	System Test and Evaluation	$ 20.3 M	$ 20.8 M	$ 21.3 M	$ 21.8 M	$ .9 M	4.5%
60000	Data	$ 6.3 M	$ 6.0 M	$ 6.3 M	$ 6.5 M	$ .0 M	0.0%
70000	Peculiar Support Equipment	$ 58.9 M	$ 57.3 M	$ 58.8 M	$ 60.3 M	($ .1 M)	-0.2%
80000	Common Support Equipment	$ .7 M	$ .7 M	$ .7 M	$ .7 M	($ .0 M)	-0.4%
90000	Initital/Replen Spares & Repair Parts	$ 9.2 M	$ 9.0 M	$ 9.2 M	$ 9.4 M	($ .0 M)	-0.1%
A0000	Depot Maint Equip and Data	$ 11.2 M	$ 10.9 M	$ 11.2 M	$ 11.5 M	($ .0 M)	0.0%
B0000	Training	$ 19.3 M	$ 19.0 M	$ 19.4 M	$ 19.9 M	$ .2 M	0.9%
C0000	Flight Supt Ops and Services	$ 31.6 M	$ 31.9 M	$ 33.2 M	$ 34.9 M	$ 1.6 M	4.9%
E0000	Transportation and Storage	$ 2.4 M	$ 2.3 M	$ 2.4 M	$ 2.4 M	($ .0 M)	-0.1%

Table 6-9 Cost Analyst's Recurring Cost Risk Summary

	RECURRING	Point	Percentile			Variance	% Diff
WBS #	WBS Element Description	Estimate	20%	50%	80%	PE Less 50%	=Var/PE
00000	Multi-Spacecraft Satellite Program	$ 4,184.5 M	$ 4,230.6 M	$ 4,344.5 M	$ 4,461.3 M	$ 160.0 M	3.8%
10000	Space Segment	$ 3,188.5 M	$ 3,225.7 M	$ 3,335.9 M	$ 3,457.8 M	$ 147.4 M	4.6%
20000	Space Vehicle	$ 3,187.3 M	$ 3,224.5 M	$ 3,334.7 M	$ 3,456.6 M	$ 147.4 M	4.6%
21000	SV Systems Engrg/Prog Mgmt	$ 93.8 M	$ 87.1 M	$ 92.5 M	$ 97.2 M	($ 1.3 M)	-1.3%
22000	Payload	$ 1,771.7 M	$ 1,786.3 M	$ 1,863.0 M	$ 1,939.8 M	$ 91.3 M	5.2%
23000	Spacecraft (Bus)	$ 1,044.8 M	$ 1,035.7 M	$ 1,099.8 M	$ 1,178.5 M	$ 55.0 M	5.3%
24000	Orbital Insertion System	$ 2.7 M	$ 2.7 M	$ 2.7 M	$ 2.7 M	$ 0 M	0.0%
25000	Support Equipment	$ 163.9 M	$ 163.9 M	$ 163.9 M	$ 163.9 M	$ 0 M	0.0%
26000	SV Integ, Ass, Test & Ckout	$ 110.5 M	$ 101.4 M	$ 108.0 M	$ 115.1 M	($ 2.5 M)	-2.3%
27000	Launch Vehicle	$ 1.2 M	$ 1.2 M	$ 1.2 M	$ 1.3 M	$ .0 M	0.0%
30000	Ground Segment	$ 161.7 M	$ 161.8 M	$ 163.8 M	$ 166.0 M	$ 2.1 M	1.3%
40000	System Engrg/Program Mgmt	$ 142.7 M	$ 142.9 M	$ 145.1 M	$ 148.0 M	$ 2.4 M	1.7%
50000	System Test and Evaluation	$ 86.6 M	$ 89.5 M	$ 92.1 M	$ 95.0 M	$ 5.6 M	6.4%
60000	Data	$ 25.9 M	$ 25.0 M	$ 25.9 M	$ 26.8 M	($ .0 M)	-0.1%
90000	Inititial/Replen Spares & Repair Parts	$ 7.6 M	$ 7.4 M	$ 7.6 M	$ 7.7 M	$ .0 M	0.1%

Table 6-10 Cost Analyst's Total Cost Risk Summary Result

	TOTAL PROGRAM	Point	Percentile			Variance	% Diff
WBS #	WBS Element Description	Estimate	20%	50%	80%	PE Less 50%	=Var/PE
00000	Multi-Spacecraft Satellite Program	$ 5,467.3 M	$ 5,574.3 M	$ 5,686.7 M	$ 5,809.2 M	$ 219.4 M	4.0%
10000	Space Segment	$ 3,974.2 M	$ 4,051.8 M	$ 4,165.3 M	$ 4,285.6 M	$ 191.1 M	4.8%
20000	Space Vehicle	$ 3,958.9 M	$ 4,036.9 M	$ 4,150.0 M	$ 4,270.3 M	$ 191.1 M	4.8%
21000	SV Systems Engrg/Prog Mgmt	$ 107.0 M	$ 100.2 M	$ 105.7 M	$ 110.5 M	($ 1.3 M)	-1.2%
22000	Payload	$ 2,232.7 M	$ 2,283.3 M	$ 2,357.0 M	$ 2,434.0 M	$ 124.3 M	5.6%
23000	Spacecraft (Bus)	$ 1,266.3 M	$ 1,263.1 M	$ 1,326.1 M	$ 1,406.8 M	$ 59.8 M	4.7%
24000	Orbital Insertion System	$ 25.6 M	$ 25.2 M	$ 25.7 M	$ 26.1 M	$ .0 M	0.0%
25000	Support Equipment	$ 187.5 M	$ 188.0 M	$ 188.6 M	$ 189.4 M	$ 1.1 M	0.6%
26000	SV Integ, Ass, Test & Ckout	$ 139.7 M	$ 130.3 M	$ 137.1 M	$ 144.7 M	($ 2.6 M)	-1.9%
27000	Launch Vehicle	$ 15.3 M	$ 15.1 M	$ 15.3 M	$ 15.6 M	$ .0 M	0.1%
30000	Ground Segment	$ 480.3 M	$ 489.2 M	$ 497.6 M	$ 505.6 M	$ 17.3 M	3.6%
40000	System Engrg/Program Mgmt	$ 161.2 M	$ 161.9 M	$ 164.1 M	$ 167.1 M	$ 2.9 M	1.8%
50000	System Test and Evaluation	$ 106.9 M	$ 110.8 M	$ 113.5 M	$ 116.3 M	$ 6.6 M	6.1%
60000	Data	$ 32.2 M	$ 31.3 M	$ 32.2 M	$ 33.1 M	($ .0 M)	-0.1%
70000	Peculiar Support Equipment	$ 58.9 M	$ 57.3 M	$ 58.8 M	$ 60.3 M	($ .1 M)	-0.2%
80000	Common Support Equipment	$ .7 M	$ .7 M	$ .7 M	$ .7 M	($ .0 M)	-0.4%
90000	Inititial/Replen Spares & Repair Parts	$ 16.8 M	$ 16.5 M	$ 16.8 M	$ 17.1 M	($ .0 M)	-0.1%
A0000	Depot Maint Equip and Data	$ 47.6 M	$ 46.9 M	$ 47.6 M	$ 48.3 M	$ .0 M	0.0%
B0000	Training	$ 48.0 M	$ 47.6 M	$ 48.2 M	$ 48.8 M	$ .2 M	0.3%
C0000	Flight Supt Ops and Services	$ 496.6 M	$ 493.7 M	$ 498.4 M	$ 502.8 M	$ 1.8 M	0.4%

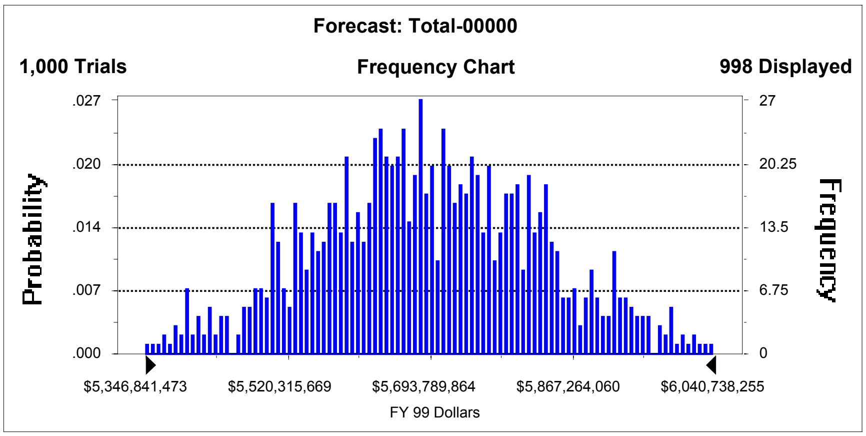
Crystal Ball Report

Forecast: Total-00000 **Cell: AO17**

Summary:

Display Range is from $5,346,841,473 to $6,040,738,255 FY 02 Dollars
Entire Range is from $5,345,703,513 to $6,047,505,132 FY 02 Dollars
After 1,000 Trials, the Std. Error of the Mean is $4,284,908

Statistics:	Value	Statistics:	Value
Trials	1000	Skewness	0.03
Mean	$5,690,754,226	Kurtosis	2.65
Median	$5,686,660,462	Coeff. of Variability	0.02
Mode	---	Range Minimum	$5,345,703,513
Standard Deviation	$135,500,688	Range Maximum	$6,047,505,132
Variance	2E+16	Range Width	$701,801,620
		Mean Std. Error	$4,284,907.97



Percentile	FY 02 Dollars	Percentile	FY 02 Dollars
0%	$5,345,703,513	60%	$5,724,405,313
10%	$5,512,029,589	70%	$5,763,867,456
20%	$5,574,256,762	80%	$5,809,176,425
30%	$5,619,526,390	90%	$5,864,661,580
40%	$5,653,042,940	100%	$6,047,505,132
50%	$5,686,660,462		

Figure 6-8 Example of Crystal Ball Software Options, Description of the Total Cost Distribution

As shown in Table 8-3, Cost Analyst's Total Cost Risk Summary Result, our total program (contractor costs) point estimate cost is $5,467.3M. The cost risk model results show a $5,686.7M 50-percentile risk cost for the total program. The deviation between the point estimate and 50–percentile risk cost is approximately $219.4M or 4%. Approximately 1.15% is attributable to Space Vehicle Recurring learning curve variances, and 2.86% due to probability cost risk factors. While risk results are shown in Table 8-3 at the major WBS element level, the cost risk model can be modified to produce risk percentiles at any WBS element level.

Conclusion

A cost risk analysis methodology has been demonstrated in detail, giving specific sample cost risk results for a multi-spacecraft satellite system in a preplanning phase for a long-term spacecraft and ground engineering, production, and replenishment program(s), including operations and support activities.

With risk, the point value, variance and underlying distributions can be quantified. We define cost risk as the quantified impact of schedule, technical, maturity, performance, producibility, supportability, and cost estimating uncertainty on cost elements at a non-summing level. For the triangular distribution, the one most frequently used, up to 21 risk levels can be entered depending on the risk range from very high to very low, and the symmetry type, skewed left or right or symmetrical. We also allow cost risk to incorporate the impact of the learning curve on the TFU cost. Varying the uncertainties of the cost probabilities and learning curves using a risk model with Monte Carlo simulations gives us statistical derived cost distributions at varying percentiles. The total program results at a particular percentile (50% in our case) subtracted from the total program point estimates gives us the cost risk of the total program.

The process of going through this extensive, iterative cost risk procedure, including cost risk scoring, applying distributions and skewedness and working closely with engineering and technical experts as described, leads the cost team to produce a realistic cost risk product. One of the main goals of this approach is to fully integrate the risk management process with the cost risk analysis in order to maintain consistency in the evaluations of risk. This consistency and iteration of cost risk with updated evaluations can also direct program management to focus on specific risk areas. At all stages in the program, the cost team provides valuable information to program managers and the customer. In many cases resources have been redirected to problem areas to retire risk early to an acceptable risk level at program decision points. This information increases a company's competitive position by assisting in their ability to recommend the most efficient system that meets the customer's budget, and by ensuring the customer that the cost provided has acceptable cost risk.

List of Acronyms and Abbreviations

AIPT	System Architecture and Design Integrated Product Team
CDR	Critical Design Review
COTS	Commercial Off-The-Shelf
EMD	Engineering, Manufacturing and Development
H/W	Hardware
LCC	Life Cycle Cost
LOE	Level Of Effort
O&S	Operations and Support
OIS	Orbital Insertion System
PDR	Preliminary Design Review
PE	Point Estimate
R&D	Research and Development
REA	Responsible Engineer Authority
RIPT	Risk Integrated Process Team
S/W	Software
SDR	System Design Review
SLOC	Source Lines of Code
SRR	System Readiness Review
TFU	Theoretical First Unit
WBS	Work Breakdown Structure

Uncertainty/Consequence Type Definitions

Definition/ Risk Factor	Major Independent Sources of Uncertainty	
	Technology (Non-Recurring)	**H/W and S/W Maturity (Non-Recurring)**
Definition	Uncertainty of system performance due to reliance on the availability and promise of technology. Technology uncertainty includes the required level of technological sophistication and reflects the current state of hardware development and testing maturity. Hardware maturity ranges from scientific research, conceptual design, brass board, breadboard, prototype, to an operational unit.	Uncertainty in ability to transform requirements into a credible design that will meet user needs. For hardware, the focus is on achieving space qualification. For software, the focus is on defining algorithms that achieve functional and performance requirements.
High **(5)**	New technology. **H/W:** Scientific research is required and ongoing. Many unresolved technical issues remain. **S/W:** Knowledge or technology necessary for application development in ongoing research.	**H/W:** Conceptual design complete. **S/W:** Algorithms will be created mostly from scratch, little or no understanding of S/W requirements, no requirements baseline.
Moderately High **(4)**	Significant modifications to existing technology. **H/W:** Development has been limited to engineering studies. **S/W:** Concept proof of principle is complete or there exists a reasonable analogy to the functionality of the application/technology.	**H/W:** Breadboard available. **S/W:** Algorithms are mostly designed but moderate development is required, questionable understanding of S/W requirements, changes in many key requirements expected.
Moderate **(3)**	Moderate modifications to existing technology. **H/W:** Significant shortfalls exist between the requirements and the performance demonstrated in existing systems. **S/W:** Critical function/characteristics demonstrated and tested in code or there exists a valid performance analogy to this technology application.	**H/W:** Brass board / prototypes are available. **S/W:** Algorithms exist but need modifications, moderately complete definition of S/W requirements, and change in some key requirements expected.
Moderately Low **(2)**	Minor modifications to existing technology. **H/W:** A successfully tested prototype is currently in existence. **S/W:** Prototype of technology in analogous application area in alpha and/or beta tests.	**H/W:** Units are currently undergoing qualification testing or are qualified but not flown. **S/W:** Straight conversion of code or rehost, algorithms exists, mostly complete definition and understanding of S/W requirements, changes in minor requirements expected.

Low **(1)**	Existing technology. **H/W:** All performance requirements have been achieved on an identical or near identical item. **S/W:** Technology in analogous application currently implemented and passes cutover into operational environment.	**H/W:** Qualified and flight Proven. **S/W:** COTS products available that meet requirements, very complete definition and understanding of S/W requirements, little or no change to requirements baseline.

Definition/ Risk Factor	**Major Independent Sources of Uncertainty**	
	Performance (Non-Recurring)	**Producibility (Recurring)**
Definition	Uncertainty of system performance due to lack of design integration and requirements verification data.	Uncertainty in ability to produce items within the program cost and schedule constraints.
High **(5)**	Performance characteristics are unknown and / or limited to invalidated analytical results. System integration issues have not been addressed.	**H/W:** Production experience has been limited to the R&D environment. Material requirements are not well defined. **S/W:** An integrated control structure for the software must be developed. Software created entirely from scratch, required engineering development is unknown.
Moderately High **(4)**	Performance of item has been established using a validated analytical tool. Minor amount of lab testing of components has been undertaken. Major technical, weight, and size issues must be addressed before the system will meet performance requirements.	**H/W:** Production has been limited to the lab environment. Most but not all materials required for the production process are known. **S/W:** Software prototypes and simulations have been used in an engineering hardware environment. Software created mostly from scratch with major engineering development using existing technology.
Moderate **(3)**	Critical performance requirements have been verified over a broad range of operating conditions through lab testing and / or a validated analytical tool. Technical, weight, size, and integration issues have been addressed but not resolved.	**H/W:** An item with similar performance has not been produced in quantity but all materials and requirements are known. **S/W:** Similar software functions have previously been used. Modifications to algorithms and S/W implementation differences are known but significant, with moderate new functionality.
Moderately Low **(2)**	Performance of item has been verified for all operating conditions and environments. All major technical, weight, size, and integration issues have been addressed and are near resolution. Current system performance meets requirements.	**H/W:** Similar item is currently in production, simple retooling and/or minor capital investment is needed. **S/W:** Equivalent S/W in another language, or significant reusable modules may be used, or COTS available for a portion of the functionality, code is translated to another language or rehosted on different machine with minimal new functionality.

		with minimal new functionality.
Low **(1)**	Performance verification is complete in item's operating environment. No technical, weight, size, and integration issues need to be addressed.	**H/W:** An identical item meeting all performance requirements is currently in production. **S/W:** Reusable or COTS software is available; almost no new coding is required to execute functions.

Definition/ Risk Factor	**Major Independent Sources of Uncertainty**	
	Supportability (Recurring)	**Cost (Non-Recurring and Recurring)**
Definition	Uncertainty to the ability to support the system during its planned lifetime and assure it can meet all availability and performance requirements. An evaluation of how well the composite of support considerations necessary to achieve the effective and economical support of a system for its life cycle meets stated quantitative and qualitative peacetime readiness and wartime utilization requirements. This includes integrated logistic support and logistic support resources related O&S cost considerations.	Uncertainty from the estimating method. The confidence in the item or system cost, as well as the LCC estimates
High **(5)**	No similar system has been fielded or developed to any substantial degree. Existing support technologies and procedures are inadequate. New technologies will be required to support the item.	Major uncertainties exist related to the scope/definition of the item to be estimated. Highly complex H/W and S/W. Achievement of cost estimate may be highly dependent on the success of other program, contractor, or government activities. Software application represents new development and no legacy can be applied to SLOC estimation process.
Moderately High **(4)**	Similar items have been under some degree of development, but not fielded. Supportability requirements may have been established to some degree. Substantial modifications to existing technologies or procedures, together with new technology will probably be required to support the item.	Cost estimate based on uncertainties in scope/definition of the item. Significant increase in complexity, major increase in software modules. Achievement of cost estimate may depend significantly on the success of other program, contractor, or government activities. Software application now represents new development and very little legacy can be applied to SLOC estimation process.
Moderate **(3)**	Items similar in concept have been supported as fielded systems during test. Substantial modifications may be required to existing support technologies or procedures to	Results from a cost model in which the estimate is feasible and the scope of the system is adequate. Moderate increase in H/W and S/W complexity and/or performance requirements. Achievement of cost estimates may be dependent on the

Definition/ Risk Factor	Major Independent Sources of Uncertainty: Supportability (Recurring)	Major Independent Sources of Uncertainty: Cost (Non-Recurring and Recurring)
	technologies or procedures to support the item.	of cost estimates may be dependent on the success of other program, contractor, or government activities. SLOC estimates based on very little appropriate legacy and no prototyping activity.
Moderately Low **(2)**	A similar item has been fielded and is being currently supported, or has been demonstrated to be supportable. Only minor changes to existing support technologies or procedures will be required to support the item.	Item cost estimate base on, or extrapolated from program actuals or supplier information for a very similar item that is already in production. Minor increase in H/W and S/W complexity or performance requirements. Achievement of cost estimate may be slightly dependent on the success of other program, contractor or government activities, SLOC estimates based on some appropriate legacy and minimal prototyping activity.
Low **(1)**	A similar item has been fielded and is being supported with an established and mature logistics system. No new support technologies or procedures are required to support the item.	Cost estimate based on vendor quotes for a well-defined item, an off-the-shelf item or a catalog price for an item. No hardware or software change is required. Achieving cost estimates is independent of the success of any other efforts. SLOC estimates are based on significant legacy and prototyping activity.

Definition/ Risk Factor	Major Indep Sources of Uncertainty: Schedule (Non-Recurring and Recurring)	Consequence Categories: Consequence
Definition	Uncertainty as to whether the specified acquisition time period is adequate compared to schedules for similar systems. Assumes that a schedule that meets program goals has been developed and the schedule contribution from the item or process under consideration is defined. Risk reflects the confidence in meeting the item or system schedule milestones.	One of two components of risk or the measurement of risk of the failure to account for the severity of the consequences of failing to achieve program objectives within defined cost and schedule constraints. Failure to account for the severity of the consequences even though the probability of occurrence is low.
High **(5)**	Major uncertainties exist related to the scope/definition of the item to be estimated. Highly complex hardware/software. Achievement of schedule estimates may be highly dependent upon the success of other program, contractor, or government activities.	The failure of the item or system to perform as required is a “show stopper” for the overall system. No alternative designs are identified. A thorough investigation of alternative concepts or technologies is required to meet operational requirements. Cost will significantly exceed budget (>10%) with consequences to unrelated efforts. Larger schedule slips will affect major milestones and

Definition/ Risk Factor	Major Indep Sources of Uncertainty Schedule (Non-Recurring and Recurring)	Consequence Categories Consequence
		schedule slips will affect major milestones and may also affect system milestones.
Moderately High **(4)**	Schedule estimate developed with uncertainties in the scope/definition of the item. Significant increase in complexity. Major increase in number and size of SW modules. Achievement of schedule estimates may depend significantly upon the success of other program, contractor, or government activities.	The failure of the item or system to meet its operational requirements will degrade the overall system performance below system specifications/requirements. Design alternatives have only been demonstrated in a laboratory environment. A significant amount of testing and investment is required before the operational requirement can be achieved. Cost will exceed budget (7 –10%) and development schedule slips will affect major milestones.
Moderate **(3)**	Results from a schedule model in which the scope/definition of the system is adequate. Moderate increase in hardware/software complexity or performance requirements. Achievement of schedule estimates may be dependent upon the success of other program, contractor, or govt. activities.	The failure of the item or system to meet operational requirements will degrade the overall system performance. Additional cost investments (5 – 7%) and schedule slips in key milestones are required to meet operational requirements.
Moderately Low **(2)**	Item schedule estimates based on, or extrapolated from, program actuals or supplier information for a very similar item that is already in production. Minor increase in hardware/software complexity or performance requirements. Achievement of schedule estimates may be slightly dependent on the success of other program, contractor, or government activities.	The failure of the item or system to meet its operational requirements may degrade the overall system performance. However, a number of proven design approaches are currently available. Minor investments (< 5%) and/or schedule slips are required to meet operational requirements.
Low **(1)**	Schedule estimates based on vendor quotes for a well-defined item, an off-the-shelf item or a catalog item. No hardware or software changes are required. Achieving schedule estimates is independent of the success of any other efforts.	Minimal or no impact to technical performance, cost, or schedule

7. Impact of Cost Risk Analysis on Business Decisions

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Abstract

The purpose of this section is to illustrate the value of cost risk-opportunity analysis to management's business decisions. These nine aerospace actual case studies show how cost risk analysis added valuable decision information and enabled the contractor and customer to avoid financial risk:

- Revise program strategy
- Drop unwise R&D project
- Avoid cost overruns
- Resist unwarranted cost reductions
- Confirm sub-contractor bids
- Reduce public profit report

"History-based estimates, with credibility and low risk" is the aerospace industry focus on cost realism. Risk identification, analysis, and control are essential to the health of a program. The object is to avoid cost surprises by proactively eliminating problems early in a program's life.

Finance and Estimating bring strong experience, tools, and methods to quantify upside-opportunity and downside-risk (e.g., parametric estimating, historical data, and Monte Carlo analysis). We must be an integral part of the team to report and control cost risk.

What's the Issue? Who Cares About Risk Analysis?

We have all met the risk analysis skeptic. These individuals either doubt that prudent cost risk analysis is feasible, or that the decision makers will pay any attention. One of their favorite taunts is, "Show me where risk-opportunity analysis made a business impact!" Perhaps these doubters have not seen effective cost-risk assessments. Or perhaps their management has closed their eyes to any answer but their own preconceived estimates.

Thus the objective of this paper: To demonstrate the impact cost risk analysis had on business decisions in nine actual cases. In each instance, cost risk assessment impacted program cost estimates and/or contract structure.

It is not sufficient for the weather forecaster to predict "rain today." Rather, we expect the weatherman to tell us "60% chance of rain today." In the same fashion, the professional cost estimator should provide cost probabilities to the business decision team.

Cost estimation and budgeting are an integral part of American business. Predicting and controlling cost is one of the cornerstones of effective business along with product performance and on-time schedules.

It is axiomatic that every "single point" cost estimate will be wrong. The question is, "How wrong." Cost estimating is a combination of science and art. Cost risk-opportunity analysis is the process of providing decision makers with both estimates and their associated probability. Each year we see improvement in cost estimating tools, data, and methods to produce more accurate, lower risk, estimates.

This paper presents a variety of cost-risk range estimating approaches and shows how they can be presented in simple fashion to the decision maker. The intent is that every Finance Estimator will know how to actively support Risk Management and thereby contribute to the financial success of their organization.

Risk Management … "No Surprises"

Cost risk analysis is one segment of the larger process of managing technical, schedule, and cost risk. Risk Management is an organized, systematic, decision-making process that …

- Efficiently identifies risks
- Assesses risk levels
- Effectively reduces or eliminates risks to achieve program goals
- Spans all phases of the program
- Is iterative
- Is not an option or a project add-on, and
- Should be tailored to the specific project

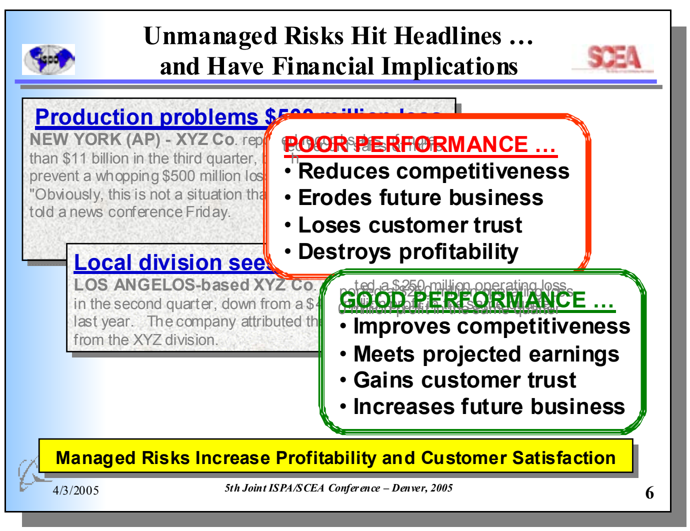


Figure 7-1 Unmanaged Risks Hit the Headlines

Unmanaged risks have negative consequences that reduce competitiveness, erode future business, and destroy profitability and shareholder confidence.

Managed risks lead to improved business performance, which results in maximized shareholder earnings.

Effective Risk Management leads to increased shareholder value. Increased shareholder value is only attained when our commitments are met on schedule, on budget, with productivity on the rise. Meeting or exceeding our product performance specifications is achieved by understanding upfront the risks we face and proactively managing those risks.

Following are some common examples of schedule, cost, and technical risks:

- The risk of a supplier **schedule** slip could translate into missing key scheduled deliveries. This could result in increased program costs, incorrect cash flow projections, and missed earnings targets.
- The risk of **technical** performance issues could result in costly design changes or the necessity for additional testing. As a result of the technical risk, cost and schedule risks may develop as well.
- Affordability **cost** improvements may result in enhanced design changes that reduce the technical, cost, and/or schedule risks.

Risk Management is one of Boeing's Program Management Best Practices. In addition, it is key to the integration of many of the Program Management Best Practices. For example, Risk Management is used for evaluations of the program configuration, technical, cost and schedule baselines under baseline management. It is key to understanding performance as demonstrated in Earned Value Management. It is a key element in Affordability and program cost trade studies. Risk is inherent in Supplier Management and Requirements Management. Risk Management should be an integral part of any program's Management Information System.

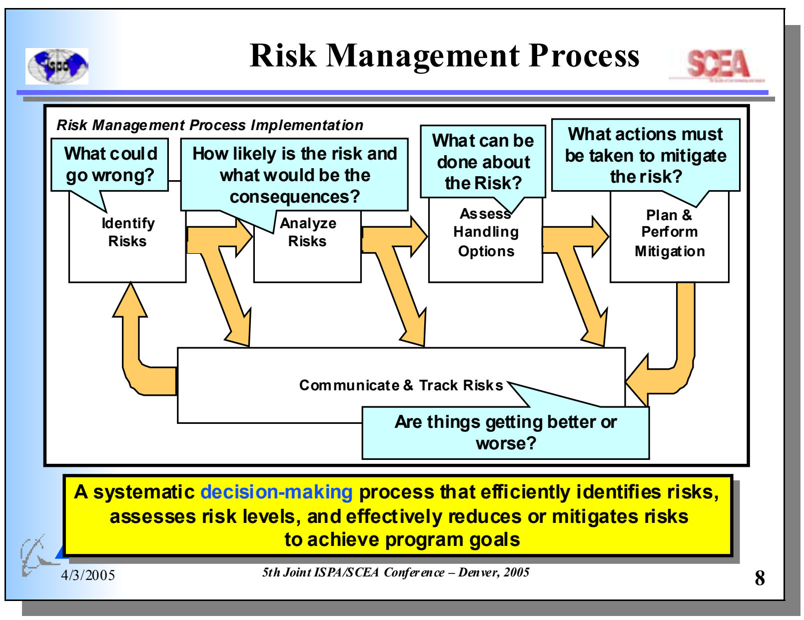


Figure 7-2 Boeing's Risk Management Process

Risk Management, Integrated Schedules, and Earned Value Management are also Finance Best Practices. Over the past several years, there have been corporate scandals that resulted in new regulations such as Sarbanes-Oxley. These regulations hold corporations accountable for the accuracy of their financial statements. Effective Risk Management reduces financial performance surprises and enables managers to make informed business decisions.

The key is no surprises!

Measuring Risk and Opportunity

A risk is an undesirable situation with a likelihood of occurring and an unfavorable consequence. Risk analysis is based on the study of two components of risk: likelihood and consequence, as seen in Figure 7-3.

- Likelihood assesses the probability that the risk will occur.
- Consequences are what may happen if the risk does occur.

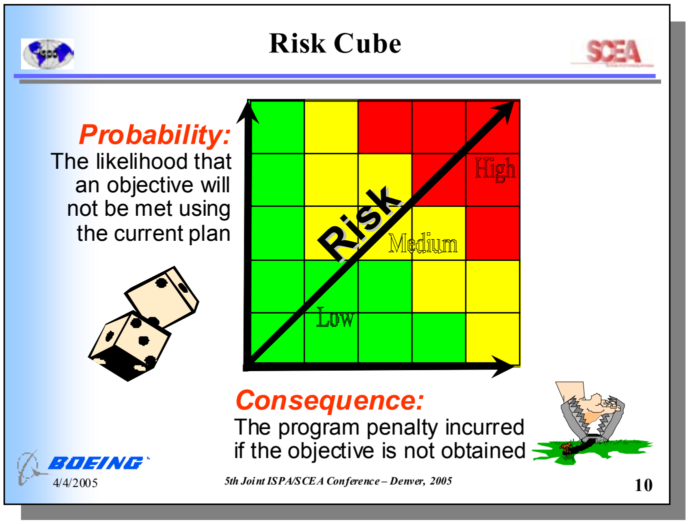


Figure 7-3 Two Components of Risk

Understanding the likelihood and consequence of a risk helps determine the severity of the risk. Conversely, an opportunity is a desirable situation with a likelihood of occurring with a favorable consequence.

There are numerous ways to evaluate risk. Three common methods are displayed in Figure 7-4.

Impact assessment. The first method is an impact assessment of both the likelihood of the risk occurring as well as the potential consequence of the risk if it is realized. The classic "risk matrix" is shown at the top right. The likelihood and consequence levels determine where the risk will be plotted on the risk matrix. This method also enables a quick visual comparison of multiple risks.

Statistical analysis of historical actuals. The second method is a historical-based approach that uses historical data and statistical analysis techniques to show the relationship of comparable historical data compared to a potential risk item. This method provides insight into potential ranges of risk as well as provides an understanding of probable outcomes.

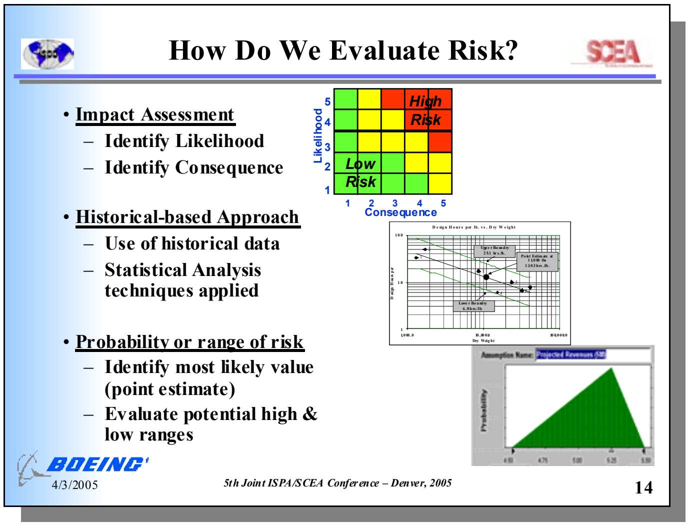


Figure 7-4 Three Means of Measuring Risk

Most likely and range. The third method of evaluating risk identifies a range of probable outcomes around a most likely estimate (point estimate). The identification of the most probable high and low value can be derived through historical analysis (objective) or expert judgment (subjective, Delphi, consensus).

These methods of risk evaluation are not mutually exclusive and are often used in combination to provide added insight into potential risks.

Impact on Business Decisions --- Industry Survey

In 1998, at the Toronto SCEA International Conference, a survey was taken of conferees to provide a broad view of cost risk assessment methods in current use. The four-page, guided questionnaire had a total of 61 responses from cost analysts in 35 government and private organizations.

One of the key findings was that roughly 75% of the organizations reported that the risk analysis findings are accepted, at least to some degree, by the management decision team. Almost half reported that the risk analysis had unqualified acceptance and was a required element of cost decisions.

One of the questions asked, "How does your organization reduce unacceptably high program risk." Two thirds of the organizations reported that they reduce program risk via further development and testing, and associated cost growth. That is, they invested more heavily in technical maturity, even if at additional expense.

The final survey question asked, "When you mitigate high cost risk, how do you typically impact the cost risk analysis?" The intent was to find out how the typical organization handles cost risk … do they hide it? Ignore it? Add cost reserves? Mitigate its causes?

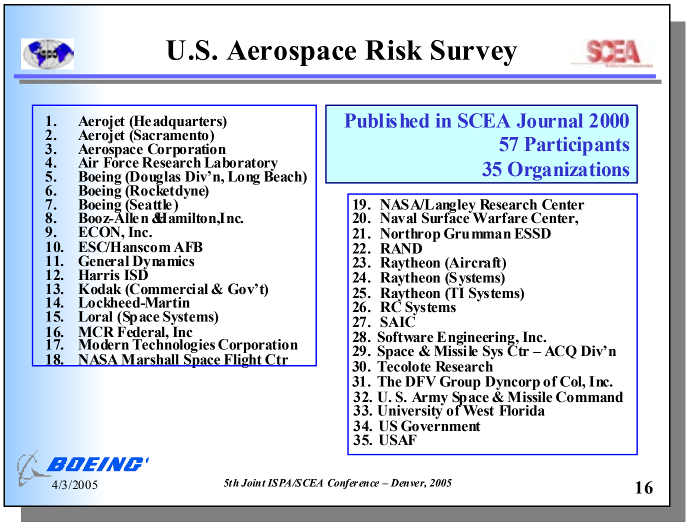


Figure 7-5 Survey Participants

Figure 7-6 summarizes the five survey responses into 3 basic strategies:

A. **30% reduce cost** … Implement lower-cost design, CAIV, program re-scoping, risk mitigation, and affordability initiatives such as design re-use.

B. **40% hold cost total** … (1) 15% hold current plan and cost and allow overruns. (2) 25% trim design costs and shift savings into risk reserves.

C. **30% increase cost or price** … (1) Increase cost base for risk mitigation actions. (2) Add profit (fee) to price to cover increased risk of overrun.

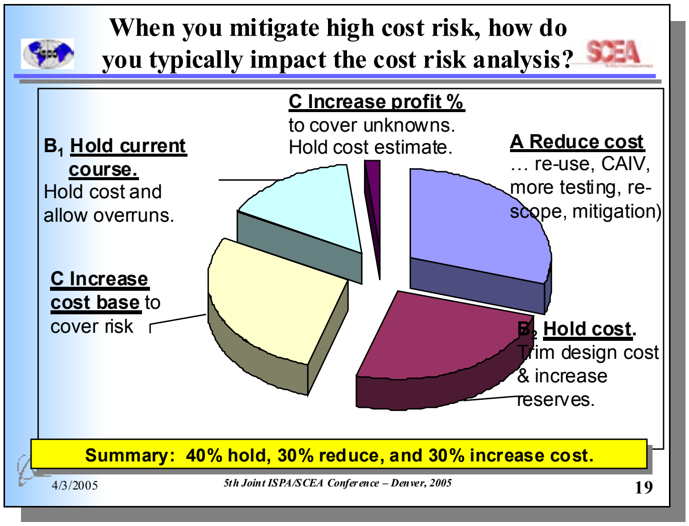


Figure 7-6 Five Ways We Handle Cost Risk

These strategies will vary, depending on the situation. It is noteworthy that about 80% of the survey responses indicated the risk assessment had an impact on the cost estimates, either to reduce or to increase. Only 20% indicated no change the program plan ("hold cost and allow overruns").

In summary, the aerospace survey indicated that management decision teams generally respond to well-founded risk assessments …

- 75% pay moderate to close attention to the assessments
- 50% view the assessment as integral to the cost analysis
- 30% will seek to reduce costs
- 25% will trim costs and shift savings into risk reserves
- 30% will add to cost and/or profit to cover higher risk

Impact on Business Decisions --- Case Studies

Recently, a Boeing-wide team met to develop risk analysis tools, methods, and training to assist all Finance employees. A key element of the risk "awareness" training is to demonstrate the benefit of cost-opportunity analysis to management decisions. Accordingly, the team gathered nine cases where cost risk analysis had a major impact on the U.S. Government or Boeing management decisions. Program names, customers, dates, and dollar values have been sanitized to protect proprietary interests. However, the situations, analysis, and resultant decisions are true to history.

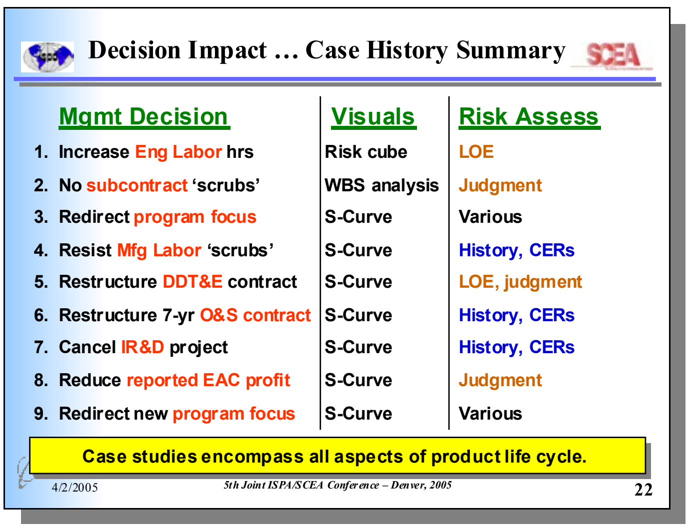


Figure 7-7 Cases Encompass Wide Variety of Management Decisions

Figure 7-7 summarizes these nine examples.

- Cases 1 and 2 are relatively simple risk assessments, rely primarily on expert judgment for cost ranges, and do not require Monte Carlo simulation. Accordingly, these two approaches are well within the capability of younger analysts using Excel tools.
- Cases 3-9 use Monte Carlo simulation, with the results displayed as probability density functions (PDF) or cumulative probability "S-curves."

Case 1: Increase proposed engineering labor hours, due to assessed risk. In this situation, the systems engineering team had identified twenty technical areas with various degrees of risk. The antenna and radio were both identified in a red-yellow-green "stoplight" risk cube. The engineering team assessed the technical risk and developed a plan to mitigate the risks and ensure mission success, as seen in Figure 7-8.

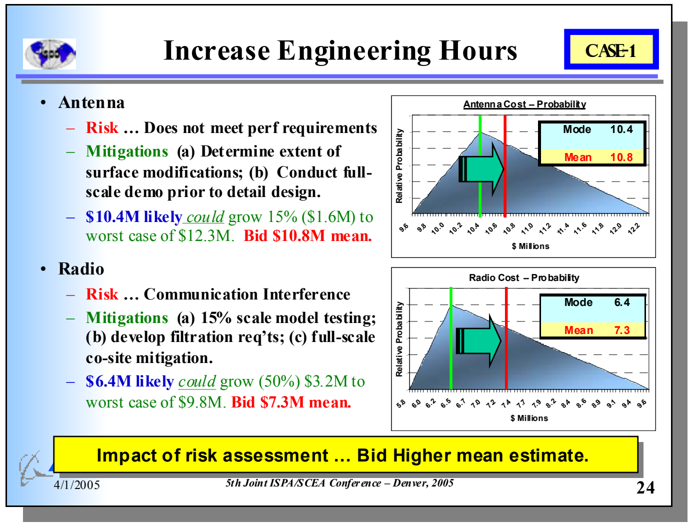


Figure 7-8 Case 1 - Increase Engineering Hours

Antenna. The cost team estimated the "most likely" antenna cost at $10.4M. The Estimating and Engineering team then estimated the worst case scenario at $1.9M (17%) higher at $12.3M, to cover mitigation plans and re-work. A simple triangular distribution was developed to represent the low-likely-high probability range. After much discussion, the team decided to bid the mean average cost of $10.8M, a bid increase of $.4M.

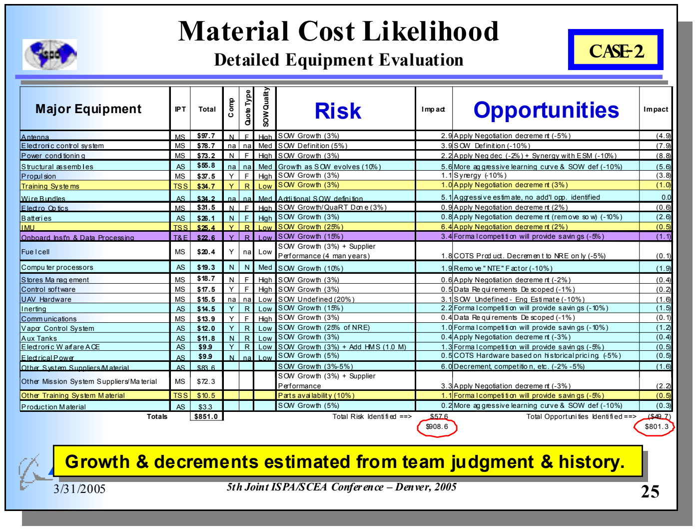
Radio. Similarly, the team developed estimates for the radio, which had significantly more risk than the antenna. The worst case was estimated $3.2M (50%) higher than the likely. The strong right-skewed probability range significantly increased the mean value ($7.3M) and the proposal was raised by $.9M to cover likely cost risk.

These two examples of judgmental risk analysis represent commonly used methods, where the estimating team had no hard history on which to judge cost range. Accordingly, they relied on experience in similar, previous work, to form the basis of mitigation plans and costs. Management confidence is increased as the mitigation plans and associated costs are developed in greater detail.

Case 2: Bid subcontract estimates without further adjustment. Figure 7-9 displays an Excel tableau for a common method of evaluating low-likely-high subcontract values. Each WBS (row) lists the likely subcontract value at the left, highest expected value in the center "Risk" section, and the lowest expected value in the right "Opportunities" section.

The low-high ranges are based upon a team of evaluators' best knowledge of the vendor, cost performance history, bidding strategies, and technical risks. As a Delphi consensus, this approach captures all of the readily available cost knowledge in a single worksheet. The column sums give management an assessment of likely cost possibility, assuming the very best and very worst combinations.

In this case, the likely value was half-way between the low-high extremes, and therefore around 50% probability. Therefore, potential cost underruns by some subcontractors would offset possible overruns elsewhere. With this risk cushion, management felt confident to bid the mid-point $851M.



Major Equipment	IPT	Total	Comp	Quote Type	SOW Quality	Risk	Impact	Opportunities	Impact
Antenna	MS	$97.7	N	F	High	SOW Growth (3%)	2.9	Apply Negotiation decrement (-5%)	(4.9)
Electronic control system	MS	$78.7	na	na	Med	SOW Definition (5%)	3.9	SOW Definition (-10%)	(7.9)
Power conditioning	MS	$73.2	N	F	High	SOW Growth (3%)	2.2	Apply Neg dec (-2%) + Synergy with ESM (-10%)	(8.8)
Structural assemblies	AS	$55.8	na	na	Med	Growth as SOW evolves (10%)	5.6	More aggressive learning curve & SOW def (-10%)	(5.6)
Propulsion	MS	$37.5	Y	F	High	SOW Growth (3%)	1.1	Synergy (-10%)	(3.8)
Training Systems	TSS	$34.7	Y	R	Low	SOW Growth (3%)	1.0	Apply Negotiation decrement (3%)	(1.0)
Wire Bundles	AS	$34.2	na	na	Med	Additional SOW definition	5.1	Aggressive estimate, no add'l opp. identified	0.0
Electro Optics	MS	$31.5	N	F	High	SOW Growth/QuaRT Done (3%)	0.9	Apply Negotiation decrement (2%)	(0.6)
Batteries	AS	$26.1	N	F	High	SOW Growth (3%)	0.8	Apply Negotiation decrement (remove sow) (-10%)	(2.6)
IMU	TSS	$25.4	Y	R	Low	SOW Growth (25%)	6.4	Apply Negotiation decrement (2%)	(0.5)
Onboard Inst'n & Data Processing	T&E	$22.6	Y	R	Low	SOW Growth (15%)	3.4	Formal competition will provide savings (-5%)	(1.1)
Fuel cell	MS	$20.4	Y	na	Low	SOW Growth (3%) + Supplier Performance (4 man years)	1.8	COTS Product. Decrement to NRE only (-5%)	(0.1)
Computer processors	AS	$19.3	N	N	Med	SOW Growth (10%)	1.9	Remove "NTE" Factor (-10%)	(1.9)
Stores Management	MS	$18.7	N	F	High	SOW Growth (3%)	0.6	Apply Negotiation decrement (-2%)	(0.4)
Control software	MS	$17.5	Y	F	High	SOW Growth (3%)	0.5	Data Requirements Descoped (-1%)	(0.2)
UAV Hardware	MS	$15.5	na	na	Low	SOW Undefined (20%)	3.1	SOW Undefined - Eng Estimate (-10%)	(1.6)
Inerting	AS	$14.5	Y	R	Low	SOW Growth (15%)	2.2	Formal competition will provide savings (-10%)	(1.5)
Communications	MS	$13.9	Y	F	High	SOW Growth (3%)	0.4	Data Requirements Descoped (-1%)	(0.1)
Vapor Control System	AS	$12.0	Y	R	Low	SOW Growth (25% of NRE)	1.0	Formal competition will provide savings (-10%)	(1.2)
Aux Tanks	AS	$11.8	N	R	Low	SOW Growth (3%)	0.4	Apply Negotiation decrement (-3%)	(0.4)
Electronic Warfare ACE	AS	$9.9	Y	R	Low	SOW Growth (3%) + Add HMS (1.0 M)	1.3	Formal competition will provide savings (-5%)	(0.5)
Electrical Power	AS	$9.9	N	na	Low	SOW Growth (5%)	0.5	COTS Hardware based on historical pricing (-5%)	(0.5)
Other System Suppliers/Material	AS	$83.6				SOW Growth (3%-5%)	6.0	Decrement, competition, etc. (-2% -5%)	(1.6)
Other Mission System Suppliers/Material	MS	$72.3				SOW Growth (3%) + Supplier Performance	3.3	Apply Negotiation decrement (-3%)	(2.2)
Other Training System Material	TSS	$10.5				Parts availability (10%)	1.1	Formal competition will provide savings (-5%)	(0.5)
Production Material	AS	$3.3				SOW Growth (5%)	0.2	More aggressive learning curve & SOW def (-10%)	(0.3)
Totals		$851.0				Total Risk Identified ==>	$57.6	Total Opportunities Identified ==>	($49.7)
							$908.6		$801.3

Figure 7-9 Bid Subcontracts Without Further Adjustment

Case 3: Redirect Program Strategy. Figure 7-10 illustrates the weakness of point estimates. In this common situation, management had been provided a series of carefully prepared point estimates (red vertical bars), but no insight on risk and probability. This case illustrates the analysis of a costly new product development, where management had to shape the bid while reducing the company's exposure to risk.

Point estimates (3a). These point estimates, based on either judgment or history, appear to describe the likely cost range. If they were carefully prepared from dependable sources, they might become the basis of an informed business decision.

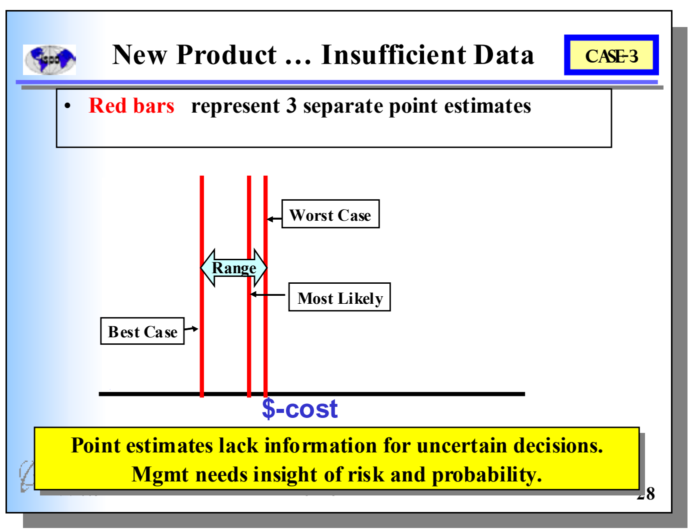


Figure 7-10 Case 3a - Redirect Program Strategy

However, if these estimates were developed with weak support, there could be false conclusions that these points represent best, worst and most likely outcomes. This illusion may jeopardize the business decision.

With the three-point assessment, management was provided with no insight into the areas of greatest cost risk/uncertainty, which was essential for this type of key procurement decision.

Probability analysis (3b). Fortunately, management sent the Estimating team back to develop a more comprehensive risk-opportunity analysis, depicted in Figure 7-11. The blue lines represent a thorough analysis of cost probability. The highest, most conservative, cost estimate (red bar furthest to the right), had only a 25% probability. That is, the project had a 75% probability of overrunning the highest point estimate.

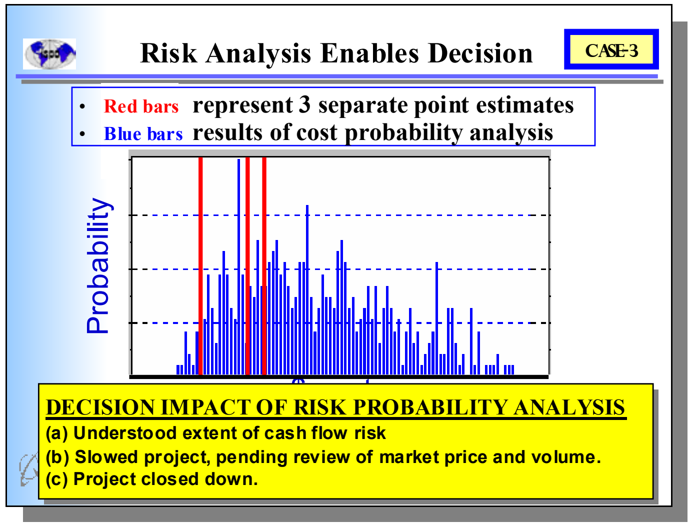


Figure 7-11 Case 3b - Redirect Program Strategy

In this real-life project analysis, management was stunned. As a result of the analysis, the business team dug deeper into the market assumptions, design architecture, and cost estimates … and discovered key weaknesses.

Ultimately, the project was wisely shut down, because the cost probabilities were too high to ensure a successful cash flow.

Case 4: Avoid decrements to proposed manufacturing labor. This case shows the power of multiple risk assessments to validate an estimate and withstand unwarranted cost cutting. Here, the proposal team had carefully developed its best, history-based, point estimate of final assembly labor hours for 130 production units. Boeing was under budget pressure to reduce the estimate, so the management team requested an independent analysis of cost probability. The Finance team chose to perform the risk assessment using parametric (historical) data.

Figure 7-12 shows two independent cumulative probability curves generated from parametric data. Each cumulative curve shows the range of costs on the x-axis, and the probability of occurrence on the y-axis.

- The left (blue) line was computed from detailed cost actuals such as factory labor, manufacturing planning, quality assurance, and other labor elements. The median forecast (50% probability) is 280,000 hours.
- The right (green) line was computed from historical factors for assembly labor as a percent of the cost of the sub-assemblies being integrated. The median (50% probability) is 330,000 hours.

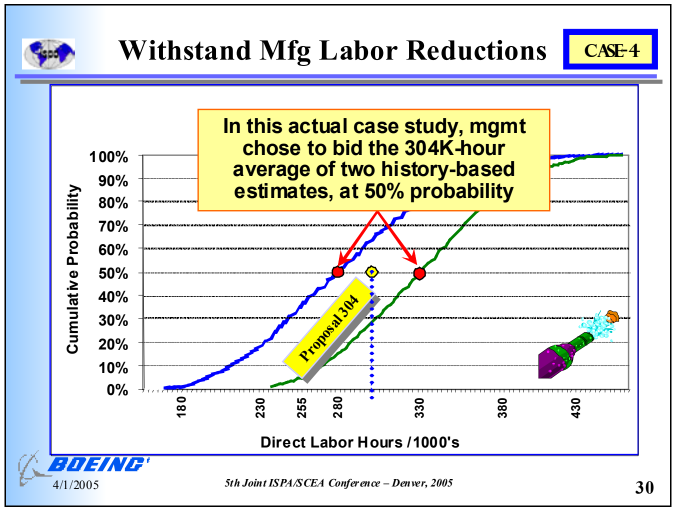


Figure 7-12 Case 4 - Withstand Labor Reduction

These two probability curves, taken from totally independent sources, depict the probability range of expected hours. These curves bounded the program estimate at 50% probability, giving management confidence to propose 304,000 hours as an acceptable risk level.

In the particular instance, the risk analysis confirmed the program bid and prevented an unwarranted labor reduction.

Case 5: Re-Direct Contract EAC and New Statement of Work. This case illustrates where the U.S. Government changed the course of a major DDT&E contract as a result of risk-opportunity analysis. The DDT&E contract was in its 9th year, with 4 years to hardware delivery. In this case, a risk assessment was performed on the program's "point estimate" for the to-go portion of the Estimate-at-Completion (EAC), $1.49 Billion.

Point estimates are the most common estimating method applied to on-going contracts. Their weakness lies in their inability to inform management of probability or likelihood. Accordingly, the U.S. Government customer requested a cost risk analysis.

So, the engineering and finance team developed a list of 20 "risky" program items, and estimated the low-high ranges around each. The sum of the lows was $1.36B and the highs $1.93B. That is, the to-go portion of the Estimate-at-Completion ranged from $1.36 to $1.93 Billion.

This simple range analysis (bold-dotted-blue-line in Figure 7-13) provided much greater insight to management; and it revealed a much greater chance of an overrun vs. an underrun. However, this picture still didn't tell the customer the estimate at 50% probability.

We all know that good events offset bad events, and that probability analysis considers the offsets. Accordingly, the customer asked Boeing to apply Monte Carlo probability analysis to the 20 risk items. This statistical analysis quantifies the offset of good and bad events and shows the relative probability. The thick red line depicted the Monte Carlo results, and showed cost really ranged from $1.45 to $1.8B, with a median ("50/50") value of $1.6B.

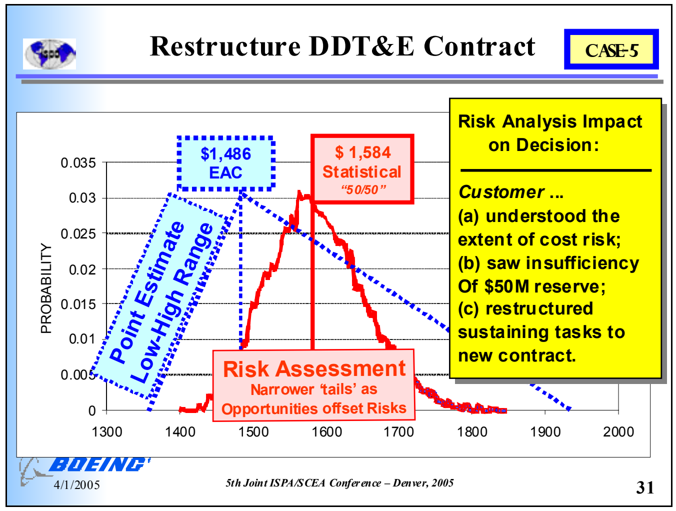


Figure 7-13 Case 5 - Redirect Estimate at Completion and New Statement of Work

This statistical median was roughly $100M higher than the program "point" estimate. This greatly concerned the customer, because the program had only $50M in reserve; and they were unwilling to request additional funding of $50M.

Once the customer understood the cost risk, they made major changes in their procurement strategy. They placed greater emphasis on cost risk mitigation and affordability initiatives. Finally, new sustaining tasks were shifted to new contracts.

Bottom line: Finance's cost risk analysis had a major impact on contract administration.

Case 6: Re-Structure 7-Year Operations Contract. This case illustrates where the U.S. Government changed its strategy for a major Operations and Sustaining (O&S) contract as a result of risk-opportunity analysis. Several years ago, the U.S. Government considered awarding a 7-year Operations contract to Boeing. Figure 7-14 summarizes the key sequence of financial events:

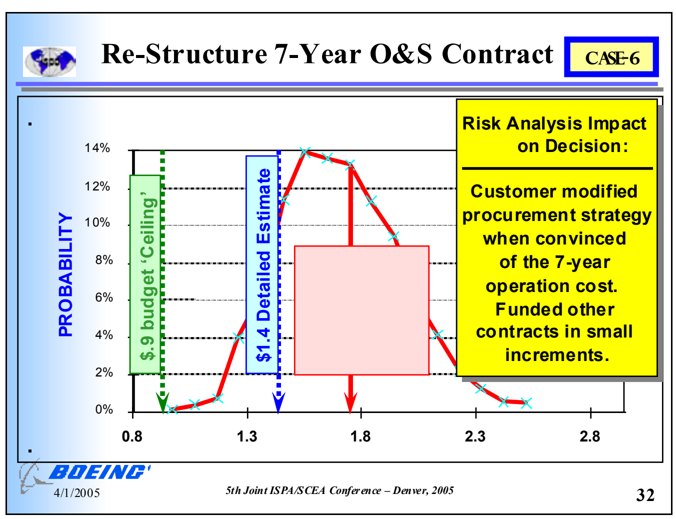


Figure 7-14 Case 6 - Re-structure 7-Year Operations Contract

- **Budget funding** was capped at $.9B (left, green vertical arrow in Figure 7-14).

- **Proposal.** The Estimating team, comprised of both Government and Boeing employees, jointly-developed a "One-Pass" proposal estimate of $1.4B (middle, blue vertical arrow). This proposal estimate was made with great care, by a large joint team, using disciplined estimating processes. Accordingly, both the Government and Boeing had confidence in its joint estimate.

The Government Program Office was in a quandary, as there was no possibility for an additional $500M funding (growth from $.9B funding to $1.4B proposal).

Accordingly, the Government requested Boeing to develop an independent cost and risk probability analysis to more confidently predict likely cost. Boeing developed two estimates from completely different historical databases. One estimate was based on sustaining costs as a function of flight weight. The other was based on analogy to a similar, previous Government program. These two estimates, when normalized to a common baseline, were within 10% of each other.

- **Risk analysis.** The bold red probability distribution depicts a very wide range ($1.0-2.4B), most likely of $1.5B, and mean expected value of $1.7B. Historical cost analysis and Monte Carlo assessment, from two difference databases, concluded there was no probability of the estimate coming under the $.9B budget limit.

After much discussion of options, the Government cancelled plans for a multi-year O&S contract. Instead, the Program Office made many, incremental contract awards, year by year.

Did risk analysis save the Government funding? We'll probably never know. But we can be assured that careful risk assessment prevented the Government from entering into a single contract award certain to overrun.

Case 7: Cancel IR&D project. Case 7 depicts the power of risk assessment when determining whether or not to pursue IR&D development of new technology. In this Boeing program, Phantom Works was seeking about $4M in IR&D funds. Figure 7-15 summarizes the three cost estimates considered by management for the IR&D go/no-go decision:

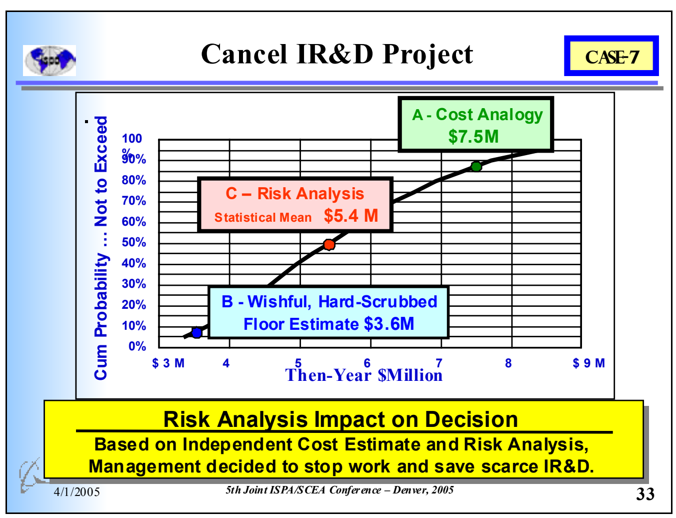


Figure 7-15 Case 7 - Cancel IR&D Project

- Point A was a recent, similar project that had spent $7.5M on developing a successful prototype flight.
- Point B was the optimistic, hard-scrubbed, engineering floor estimate of $3.6M.
- Point C was the median (50%) point on the history-based, cost risk assessment.

Management had been very skeptical of the optimistic engineering estimate of $3.6M; and requested an independent, parametric, probability analysis, Point C. The mean ("expected") value of $5.4M was $1.8M (50%) higher than the floor estimate. Furthermore, the probability analysis showed only a 7% chance that the $3.6M estimate could be achieved.

The Risk Analysis impact was that management wisely chose to shut down the project and divert the IR&D funds to projects with more value to the Boeing Company.

Case 8: Reduce Reported Estimate-At-Completion (EAC) Profit. Case 8 illustrates the reduction in externally-reported forecast profits, due to underlying risk of cost overruns in a 70/30 share contract. This example illustrates the benefit of risk analysis on profit planning and disclosure.

The blue "ski slope" in Figure 7-16 depicts the probability of various levels of program profit. The program estimated baseline profit of $42M, or 8% over baseline cost. But the probability analysis showed there was only a 25% chance of achieving this $42M profit.

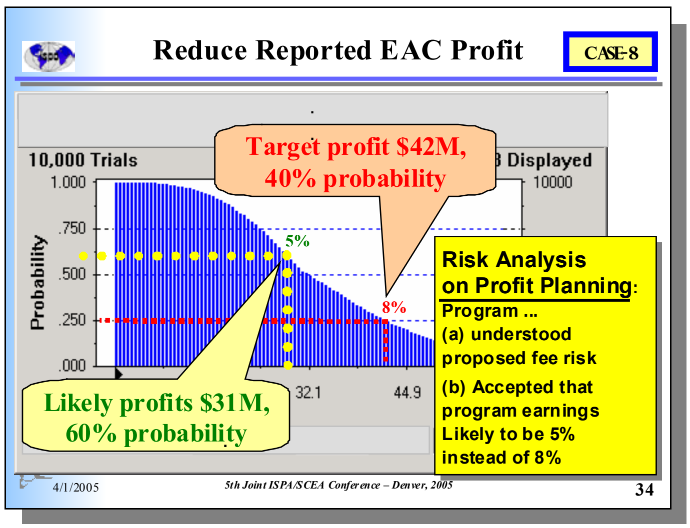


Figure 7-16 Case 8 - Reduce Reported Profit

Upper management was very uncomfortable with only a 25% likelihood; and asked the program to project a lower dollar profit with a higher probability of 60%, for the Quarterly Operating Plan. Accordingly, the program projected a profit of $31M, or 5% over cost, with a 60% probability.

Based upon this analysis, upper management agreed to project the lower $31M earnings in the quarterly financial projections. At the time, this was a major concession, however, it is important to provide honest financial predictions and disclosures, as seen in the Sarbanes-Oxley ("SOX") initiatives.

Carefully prepared and presented cost risk analysis was the key to lowering management profit expectations.

Case 9: Redirect new program focus. Case 9 shows an example where new-business focus is radically shifted from cost issues to market-volume-price concerns. New products face major risk in cost and capital, yet even higher risk in market volume and price. For over 30 years, America's commercial enterprises have used risk analysis of cost and new venture cash flows to better understand the probability of financial success.

Not long ago, Boeing assessed one of its new commercial ventures, probing to find the weakest points in the cash flow. Figure 7-17 shows the program cost point estimate of $11.8 at only 39% probability. That is, there was a 61% chance costs of overrun … far too great a financial risk.

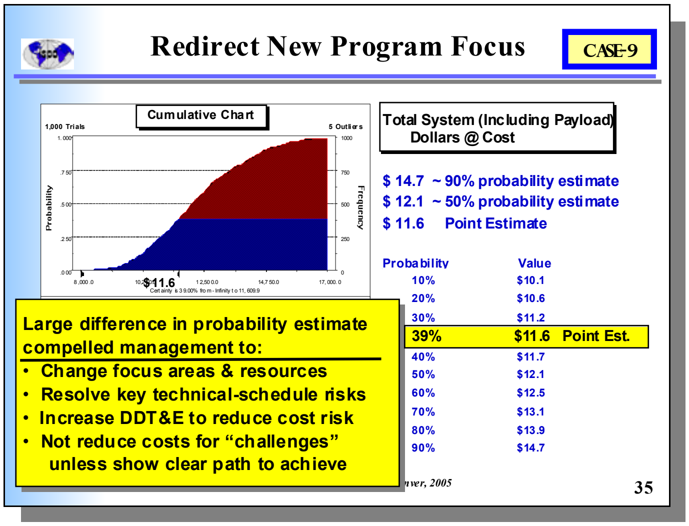


Figure 7-17 Case 9 - Redirect Program Focus

"Tornado" charts and sensitivity analysis were used to prioritize the financial risk issues. The team evaluated all aspects of the technical maturity, propulsion, software, capital investment, flyaway costs, improvement curves, and market issues. The probability analysis showed market price-volume to be more important than cost risk.

As a result of the financial risk assessment, the management team changed project focus, pinpointed key technical risks, and increased DDT&E investment. Further, they refused to trim cost estimates in "challenge" areas unless ample proof was offered. Risk-opportunity analysis played an essential role is shaping the development of this new product; and the Estimating and Finance employees played a vital part of the product team.

Summary

These nine actual cases illustrate the impact cost risk-opportunity analysis can have on Government and Contractor business decisions, and cover all facets of the business life cycle:

- Program phases … IR&D, DDT&E, production, and operations
- Pre- and post-contract award
- Cost elements …engineering, manufacturing, sub-contractor, and sustaining
- Sectors … Government and commercial

Cases 1 and 2 are relatively simple risk assessments, rely primarily on expert judgment for cost ranges, and do not require Monte Carlo simulation. Accordingly, these two approaches are well within the capability of younger analysts using Excel tools. Cases 3-9 use the more sophisticated Monte Carlo simulation, with the results displayed either as probability density functions (PDF) or cumulative probability "S-curves."

Following are the key lessons from these actual case histories:

- **Revise new program strategy.** The great weakness of the best "point" estimates to support complex new business strategies (cases 3 and 9)

- **Resist unwarranted cost reductions.** The power of multiple risk assessments to withstand unwarranted cost cutting (case 4)
- **Avoid cost overruns.** The ability of risk analysis insight to effect major swings in the U.S. Government contract strategy and avoid almost certain cost overruns (cases 5 and 6)
- **Drop unwise R&D project**. The benefit of risk assessment to shed light on unwise IR&D projects (case 7)
- **Reduce public profit report.** Appropriate reduction of externally-reported profit in light of significant cost risk (case 8)

The chief objective of these cases has been to encourage the reader to avoid the perils of "point estimates" which do not show the probability and range of possible outcomes.

Recommendations to Finance-Estimating Professionals. Finance and Estimating team members have unique skills and tools to quantify upside-opportunity and downside-risk. We have immediate access to cost history, sound cost estimating relationships (CERs), powerful cost tools, and cost models.

We have a network of skilled colleagues, in our own company or across the industry, to share data and tools. The industry professional associations are a ready means of accessing non-proprietary information. Accordingly, you will personally benefit from membership and participation in the International Association of Parametric Analysts (ISPA), Society of Cost Estimating and Analysis (SCEA), and the Space Systems Cost Analysis Group (SSCAG).

We have the professional responsibility to assist in identifying and measuring both risks (to program health) and opportunities (to exceed the baseline plan). We are an integral part of the team to implement and monitor the correct program risk mitigations.

Each of us has an important part in assuring the continued financial health of the business, enhancing shareholder value, and protecting the interests of government and commercial customers. Risk-opportunity analysis is one of the core tools in our financial arsenal.

Constructing a Cost Risk Estimate

8. Some Approaches to Cost Risk Analysis

Timothy P. Anderson
The Aerospace Corporation

Nick Lozzi
Tecolote Research, Inc.

NRO Cost Group Method

Following is an outline of the NRO Cost Group (NCG) method for developing a complete, risk-adjusted cost estimate [1].

1. **Define the "baseline" program.** This is the program "as specified" by the program office and the contractor. The "baseline" cost drivers are the basis for the cost estimate.
2. **Quantify *cost modeling uncertainty* of all estimating methods.** Each CER, cost factor, or other estimating method should be statistically derived, with knowledge of the mean and standard deviation, as well as the type of distribution (normal, lognormal, etc.). This will facilitate quantification of *cost modeling uncertainty*.
3. **Determine, or estimate, inter-WBS element correlations.** This can be done using Covert's method [2] for certain cost models, or they can be estimated using a method such as that in Table 2-2.
4. **Produce "baseline" cost estimate using Monte Carlo simulation.** Enter the WBS into a Monte Carlo simulation framework using a simulation package such as Crystal Ball® or @RISK®. Model each CER using the appropriate probability distribution. Be sure to include inter-WBS element correlations. Run at least 10,000 iterations using the Latin Hypercube technique. The mean of this distribution serves as the *"baseline expected cost."*
5. **Quantify *cost driver uncertainty* and any *potential risk events*.** Each CER input variable should be evaluated to determine a reasonable probability distribution. This will facilitate quantification of *cost driver uncertainty*. Any potential risk events for which a cost assessment is desired should also be added to the estimate.
6. **Produce "risk-adjusted" cost estimate using Monte Carlo simulation.** Repeat step 4, with the addition of random CER input variables. Upon completion of Monte Carlo simulation, use distribution-fitting algorithms to fit a probability distribution to the resulting histogram. The mean of this distribution serves as the *"risk-adjusted cost."*
7. **Graph the PDF and CDF of the "risk-adjusted" cost estimate.** Since we estimate a *distribution* rather than a *number*, a graphical representation of the risk-adjusted cost distribution is useful.
8. **Assess "risk dollars."** The difference between the "risk-adjusted" mean and the "baseline" expected value represents the estimate of "risk dollars." These "risk dollars" can then be allocated downward to any level of the WBS using a variety of simple approaches.
9. **Assess "cost risk."** Given the PDF of the "risk-adjusted" cost distribution, the area under the PDF to the right of the cost estimate or budget represents "cost risk." The lower the cost or budget relative to the cost distribution, the higher the "cost risk."

Air Force SMC Method

Consistent with the belief that cost estimating is an art, not a science, the Air Force does not mandate one risk analysis method over another; instead it allows the estimator to customize the approach to the unique program. Many estimators use automated risk assessment tools available either commercially or through Air Force-sponsored projects. The following steps outline a general approach for conducting a risk assessment on Air Force programs.

Step 1 – Complete the Point Estimate: The program baseline is defined by the System Program Office (SPO) design team and/or Hardware contractor. The SPO design is typically a "notational" design and represents a general average of the capabilities and approaches of various potential competing contractors. Contractor designs are typically more focused on individual contractor approaches and capabilities. The nature of the design and purpose of the estimate are major considerations in both the point estimate and associated risk assessment. Point estimates are predominately estimated at the component level and attempt to capture the most likely cost for each WBS element. The estimating team must insure methodologies are appropriate to the given system and have a sound understanding of how the system compares to the technologies and contractor capabilities captured in the database or underlying methodologies.

Step 2 – Specify the Cost Estimating Risk: Determine distribution type and bounds based on the statistics associated with each methodology – a cost distribution is applied to all methodologies. The preferred method is to calculate Prediction Intervals (PI) that take into account the standard error, number of data points, and location of input parameter relative to the methodology data set. The bounds are typically modeled as a percentage of the point estimate and are specified at a given confidence level. For single point analogies or very limited data sets, grass root, and engineering build up types of methodologies, the distribution bounds are typically based on data extrapolation and engineering judgment.

Step 3 – Specify Configuration Risk: Configuration risk is typically evaluated and modeled through two aspects. The first aspect is to established distribution bounds around the methodology inputs (design parameters) to capture variability in the design. Correlations of various strengths are then incorporate between the design parameters to capture interdependencies inherent with the system design. These correlations are based on both calculated values from historical databases and engineering judgment relative to a given system. Weight/technical contingency and software code growth are always included in the methodologies used to establish the point estimate. The second aspect of configuration risk is to assess the impact of weight growth and configuration changes (i.e., 1 antenna vs. 2 antennas). This evaluation is typically handled through risk excursions to assess impact for decision makers (see step 6).

Step 4 – Specify Schedule/Technical Risk: Schedule and technical risk are typically assessed and modeled together – captured through a separate distribution than the cost distribution. Technical and Schedule risk are evaluated and modeled at the component level. Deferent approaches are applied to assess schedule and technical risk depending on the specifics of a given program. Default distributions may be utilized to capture various classifications of risk (i.e., low, medium, high,…). Classification assignments are based on a sound understanding of both the database used to develop methodologies as well as the system being estimated. In some cases, cost distributions may be modified or a penalty factor is applied to the cost distribution to capture the impacts on schedule and technical risk.

Step 5 – Incorporate Risk Results in the Point Estimate: Risk is incorporated in the point estimate either on a separate row (WBS) or allocated across the lower levels. Although the true output of the risk assessment is a distribution of possible outcomes, the point estimate is adjusted to represent a given confidence level (typically specified in the ground rules and assumptions). Additional insight into the spread associated with the risk assessment must be presented/documented.

Step 6 – Evaluate Results/Perform Sensitivity Analysis: Ensure the risk adjustments are logical and that there is a reasonable range around the total point estimate for the associated system. Understand the extent of how key risk areas (major cost drivers) impact the risk assessment. Perform sensitivity analysis to evaluate impact of different configurations and major baseline changes – what level of historical weight / cost growth was considered in the point estimate. It is also essential to assess requirements stability and how changes may impact of design approach.

Step 7 – Document Risk Assessment: Since the risk assessment provides a range of possible outcomes, it is essential to present the results in a cumulative distribution function (S-curve) and probability histogram. These charts can be developed at the total level or broken down to the level the program will be managed (appropriation, segment…). The documentation must provide an overview of the risk tool, ground rules and assumptions, and a clear justification for the basis of all risk distributions. The results and impacts of all sensitivity analysis and risk excursions must be clearly identified for the decisions makers.

References

[1] Anderson, T.P., "NRO Cost Group Risk Process," *The Aerospace Corporation*, 72nd Military Operations Research Society Symposium, Monterey, CA, June 2004.

[2] Covert, Raymond .P.,"Comparison of Spacecraft Cost Model Correlation Coefficients," *The Aerospace Corporation*, SCEA National Conference, June 2002.

9. The 11 Tenets of NASA Cost Risk

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Introduction

This NASA cost-risk section will attempt to provide the reader with more details on the processes that can be used to implement credible cost-risk assessment for NASA space systems. Since cost-risk assessment considerations cover many related topics, this section provides 11 generally held beliefs or tenets of NASA cost-risk. These tenets of NASA cost-risk are intended to convey what the NASA cost estimating community fundamentally believes about cost-risk assessment and underpin its implementation. The examples and methods illustrating how a cost estimator might implement a particular tenet are presented for basic understanding and do not necessarily represent the only way to implement a tenet. This NASA cost-risk section will expand on the 11 tenets and the NASA Cost Estimating Handbook, available at www.ceh.nasa.gov, contains much valuable reference material on cost-risk assessments that the reader is strongly encouraged to read.

The 11 General Tenets of NASA Cost Risk

1. NASA cost-risk assessment, a subset of cost estimating, supports cost management for optimum project management;

2. NASA cost-risk assessment is based on a common set of risk and uncertainty definitions;

3. NASA cost-risk is composed of cost estimating relationship (CER), parameter input and programmatic/technical risk assessment plus cost element/parameter input correlation assessment;

4. NASA cost-risk assessment is a joint activity between subject matter experts and cost analysts;

5. NASA programmatic/technical cost-risk assessment combines both probabilistic and discrete cost-risk assessments;

    - Both assessments are accomplished in parallel;

    - **Probabilistic programmatic/technical cost-risk assessment** results in risk-driven cost distributions at some level of system breakdown (e.g., WBS element). These distributions will subsequently be statistically summed for total system distribution identification (e.g., Monte Carlo simulation);

    - **Discrete programmatic/technical cost-risk assessments** involve identifying and cost estimating specific cost-driving programmatic/technical risks. Instead of probabilistic distributions and Monte Carlo simulations, however, mitigation costs for these risks are estimated based on their probabilities of manifesting discrete changes in the technical parameters (e.g., increased component mass or power regulation) and cost results compared to probabilistic cost results;

6. NASA cost-risk probability distributions are justifiable and correlation levels are based on actual cost history to the maximum extent possible;

7. NASA cost-risk assessment ensures cost estimates are “likely-to-be” vice “as specified” for optimum credibility;

8. NASA cost-risk assessments account for all known variance sources and include provisions for uncertainty;

9. NASA cost-risk integrates the quantification of cost-risk and schedule risk by enlisting the support of NASA schedule and EVM analysts;

10. NASA decision makers need to know:

    - How much money is in the estimate to cover risk events;

    - To which WBS elements are they allocated; and,

    - The confidence level of the estimate;

11. NASA project cost-risk data, collected as a function of government and contractor project estimates and actuals, contract negotiations and contract data requirements descriptions (DRDs), is compiled into the One NASA Cost Estimating (ONCE) database.

Expansion of the 11 General Tenets of NASA Cost Risk

1. NASA cost-risk assessment, a subset of cost estimating, supports cost management for optimum project management.

    - Steps 4 and 5 of Continuous Cost-Risk Management (CCRM)[1], a cost management architecture supporting the NASA project management process, represent NASA cost-risk assessment. They are perhaps the two most vital steps in the whole CCRM for they lay the all-important foundation for the subsequent cost-risk *feedback* provided in later CCRM steps that involves earned value, updated life cycle cost estimate “S”-curves, risk management reporting, probabilistic risk assessment, and schedule risk analysis. Establishing the expectations for cost impacts due to risk early in the cost management process provides a reference baseline against which actual cost-risk performance can be measured. This is valuable in providing “triggers” to project managers that application of risk reserves is required. It is also valuable to cost-risk estimators by providing validation that cost-risk distribution estimates were accurate (or not). This helps validate/update cost-risk distribution development algorithms.

    - These two CCRM steps also provide a forum for quantifying subjective risk assessments. The dialogue between cost estimators and engineers working together discussing WBS element risks is a uniquely synergistic experience that is very productive in understanding both the effects, as well as a deeper understanding, of the risks themselves.

2. NASA cost-risk assessment is based on a common set of risk and uncertainty definitions[2].

    - Uncertainty is the indefiniteness about the outcome of a situation - it includes favorable and unfavorable events. We analyze uncertainty for the purpose of measuring risk! In systems engineering this analysis might focus on measuring the risk of *{failing to achieve performance objectives}*, *{overrunning the budgeted cost}*, or *{delivering the system too late to meet user needs}*; these are examples of three unfavorable events.

    - Cost Uncertainty Analysis is a process of quantifying the cost impacts of *uncertainties* associated with a system’s technical definition and cost estimation methodologies.

- Risk is the chance of loss or injury. In a situation that includes favorable and unfavorable events, *risk is the probability an unfavorable event occurs.*

- Cost Risk is a measure of the chance that, due to unfavorable events, the planned or budgeted cost of a project will be exceeded.

- Cost Risk Analysis is a process of quantifying the cost impacts of *risks* associated with a system's technical definition, cost estimation methodologies, programmatic/technology cost-risk drivers and correlation assessment. We do the analysis to produce a defensible assessment of the level of cost to budget such that this cost has an acceptable probability of not being exceeded.

3. NASA cost-risk is composed of cost estimating relationship (CER), CER parameter input, and programmatic/technology risk assessment plus cost element/parameter input correlation assessment influenced by other programmatic risk factors.

   - Cost estimating relationship (CER) risk is the risk inherent in the cost estimating methodology. For example, if a regression-based cost estimating relationship (CER) is used, it has an associated standard error of the estimate (SEE), confidence intervals and prediction intervals, any of which can be used to include cost estimating methodology risk in the estimate.

   - CER parameter input risk is that risk brought into cost-risk by the uncertainty in the projected final value of that parameter. For example, many CERs require mass as a deterministic input when the best an engineer can do is give a range rather than a deterministic value for mass. In that case, a statistical distribution of potential values is the most credible input for mass in that CER. The uncertainty in the parameter value is thus also a part of NASA cost-risk.

   - Programmatic/technology risk is the inherent KEPP risk in WBSs assessed relative to technology, design/engineering, integration, manufacturing, schedule, project "jointness" with other NASA organizations and external agencies, competency of management team, maturity of a system architecture, requirements stability, complexity, etc., cost-risk driver categories. Quantifying the cost impacts due to programmatic/technology risk is not as statistically derivative as CER risk. For this source of risk a commonly used technique involves constructing a two-dimensional matrix where the rows are "programmatic/technical" risk source drivers such as state of the art, design/engineering, integration, etc., and the columns are intensities such as low risk, medium risk, high risk, etc. WBS elements are assigned an intensity rating for each programmatic/technical risk source driver[6,7]. A technique to be described in detail in Tenet 5 below, known as Relative Risk Weighting, adds a dimension for describing worst case, best case, and reference case scenarios with respect to various cost-risk drivers. This three-dimensional matrix produces relative risk scores for each scenario from which can be derived cost-risk adjustment factors for constructing triangular work breakdown structure (WBS) cost-risk distributions.

   - Correlation risk assessment determines to what degree one WBS element's change in cost is related to another's and in which direction. For example, if the cost of the satellite's payload goes up and the cost of the propulsion system goes up then there is a positive correlation between both subsystems' costs. Many WBS elements within space systems have positive correlations with each other and the cumulative effect of this positive correlation tends to increase the range of the possible costs.

4. NASA cost-risk assessment of programmatic/technology cost-risk drivers is a joint activity between subject matter experts (e.g., engineers) and cost analysts.

- Since cost estimators are not expert in every conceivable space system, they must work with the engineers who are the experts. The cost estimator's job, when working with the engineering experts, is to elicit risk information in a form she can translate into cost impacts. Discussions can take the form of interviews about the risks in a given WBS element and how *relatively risky* that WBS element's worst case (pessimistic), best case (optimistic) and most likely case (reference) scenarios are. This Relative Risk Weighting (RRW)[3,4] process is a suggested method in order to first, get the engineers to characterize the WBS element in terms of the their key engineering performance parameters (KEPPs[5]) that will be affected by programmatic/technology cost-risk drivers and second, develop pessimistic, optimistic and reference scenarios in terms of a WBS element's KEPPs and rate these scenarios with respect to appropriate programmatic/technology cost-risk drivers (e.g., technology level (TRL), design/engineering, schedule, integration, etc.). If possible, it is preferred to have more than one engineer in the assessment due to the discussions that naturally evolve. These discussions usually produce a synthesis assessment that is of a higher quality than just using one engineer due to the different perspectives each engineer brings to them.

- Once the cost estimator tallies the relative risk-rating scores, they are made available to the engineer for a sanity check. These relative risk-rating scores for each scenario provide the basis for developing cost-risk triangular distributions. If the results need improvement, the engineers are there to make the sensitivity adjustments. A very important by-product of these discussions is the identification of risks in each element's KEPPs for the application of mitigation funding. The identification of discrete risks is very important when justifying the total risk reserve to decision makers who need to know specific reasons why risk dollars should be made a part of the budget request. These discrete risks flow naturally out of the KEPPs identified in the risk scenario development.

5. NASA programmatic/technical cost-risk assessment combines both probabilistic and discrete programmatic/technical risk assessments

   - Both assessments are accomplished in parallel;

   - ***Probabilistic cost-risk assessment*** results in CER estimating, parameter input, programmatic/technology risk-driven distributions at some level of system breakdown (e.g., WBS element) along with correlation analysis. These distributions will subsequently be statistically summed for total system distribution identification (e.g., Monte Carlo simulation) expressed as a total cost "S"-curve.

   - ***Discrete programmatic/technical cost-risk assessments***[2] involve identifying and cost estimating specific cost-driving programmatic/technical risks. For example, a notional new electronic component for a spacecraft might have risk in KEPPs such as dynamic load resistance, operating voltage, power regulation, radiation resistance, emissivity, component mass, operating temperature range and operating efficiency. Technical staff might identify these KEPP risks during an RRW cost-risk assessment when evaluating the three WBS element risk scenarios. Instead of probabilistic distributions and Monte Carlo simulations, however, mitigation costs for these risks are estimated based on their probabilities of manifesting discrete changes in the KEPPs (e.g., increased component mass or power regulation);

   - A recommended approach to identifying and assessing programmatic/technology risks that may drive costs begins with developing *cost-risk driver rating templates.* This approach is not the only valid way to do a programmatic/technology cost-risk assessment, however, it is presented here because it addresses all of the major elements involved in programmatic/technology cost-risk assessment. Foremost among these major elements is the ability to create credible and defensible inputs to the monte carlo simulation calculators like @RISK™, Crystal Ball™ and ACEIT, avoiding the "garbage in, garbage out" syndrome. It is also presented here for the cost estimator who finds himself in the position of defending all aspects of a cost-risk assessment. Decision makers prefer, as a general rule, lower estimates to higher ones. The reason is fairly obvious. If estimates are lower, either more projects can be developed within limited available funding or proposed projects are more appealing to funding appropriators (or both). Cost-risk assessments generally add to estimated project costs so decision makers will want justification before agreeing to cost-risk assessments. The cost estimator needs a methodology that produces a cost-risk assessment that is beyond reproach. The comprehensive methodology presented here achieves that goal.

- Pre-established and well-defined risk driver categories function as criteria against which pessimistic, optimistic and reference WBS element scenarios can be evaluated. Some examples of such criteria and intensity rating scales for technology state of the art, design/engineering, complexity and interaction/dependencies are presented in Figure 9-1 through Figure 9-5 below. It is important to note that not all WBS elements need to be rated against these four specific criteria. The general rule is that whatever cost-risk driver categories are relevant to the WBS element being rated are the ones that should be used. This may involve developing different risk driver categories such as *integration, schedule, manufacturing*, etc., with associated definitions for both the cost-risk driver and the intensity scales used to rate the degree of risk level involved for the pessimistic, optimistic and reference scenarios. These cost-risk driver templates are the foundation for the interactions between the cost estimators and engineers in determining risk levels in each risk scenario for later use in quantifying their cost impacts.

Risk Category Assessment Templates

Cost-Risk Driver Category	Level of Uncertainty: Very Low	Low	Moderately Low
	Rating		
Technology: Uncertainties to system performance due to reliance on the availability and promise of technology. Technology uncertainty includes the required level of technological sophistication and reflects the current stage of hardware development and testing maturity. Hardware maturity ranges from scientific research, conceptual design, brassboard, breadboard, prototype, to an operational unit. Technology risk analysis is performed at the subsystem or lower (e.g., assembly) level. (**S/W:** Uncertainties due to availability and status of concepts and algorithms required to satisfy system performance. Technology uncertainty includes the current stage of concept and algorithm development and testing maturity. Maturity ranges from scientific research, conceptual design, proof of principle completed, prototype built, to operational. Technology risk is performed at the software item level or lower level.)	Hardware is currently operational and deployed. (**S/W Tech**: S/W is currently operational and deployed.)	Hardware is in limited production and has passed all acceptance tests. (**SW Tech:** Software successfully implemented, requires qualification.)	Prototype is currently in qualification tests, but has passed performance requirements. (**S/W Tech:** A prototype has been built and meets program requrements.)

Level of Uncertainty: Moderate	Moderately High	High	Very High
Rating			
A brassboard example has been fabricated and tested for performance and qualifications. (**S/W Tech:** Critical algorithms, functions, and characteristics demonstrated by a prototype.)	Critical functions/characteristics have been demonstrated by a brassboard example. (**S/W Tech:** Conceptual design formulated and tested for performance considerations; proof of principle completed.)	Conceptual design formulated and tested for performance and qualification considerations. (**S/W Tech:** Conceptual design formulated.)	Scientific research is required and ongoing. (**S/W Tech:** Scientific research on-going, new algorithm concept needed.)

Note: Other rating scales exist, e.g., Maxwell Risk Matrix[2]

Figure 9-1

Risk Category Assessment Templates
WBS Design and Engineering Risk Scale

Cost-Risk Driver Category	Level of Uncertainty: Very Low	Low	Moderately Low
	Rating		
Design and Engineering: Uncertainties in system performance due to uncertainties and variability in design and engineering process. Design and engineering uncertainty reflects the degree of difficulty to advance the current state of the art for a given item (e.g., subsystem) to the required, final state (e.g., qualified off-the-shelf item that meets all requirements). Design and engineering risk analysis is performed at the subsystem or lower (e.g., assembly) level. (**S/W:** Uncertainties in system performance due to variabilility in the needed design and engineering. Design and engineering uncertainty reflects the degree of difficulty to advance currently available software (potentially none to off-the-shelf) for a given item (or lower level) to the required final state needed to satisfy system requirements. Design and engineering risk is performed at the software item level or lower level.)	Qualified off-the-shelf item that meets all requirements. (**S/W D/E:** Qualified item exists that meets all requrements.)	Off-the-shelf items that require qualification. (**SW D/E:** Item exists, requires qualification or NDI item(s) with minor modifications/new development to achieve operational status)	Design effort required using standard, existing components within their original specification levels. (**S/W D/E:** Rehost or language conversion required using existing components within their original specification levels.)

- Other risk categories such as complexity, reliability, S/W, production, manufacturing, integration, etc.
  - Whatever is appropriate for WBS element

Figure 9-2

Risk Category Assessment Templates

Level of Uncertainty			
Moderate	Moderately High	High	Very High
Rating			
Design effort required using standard, existing components beyond their original accepted specification levels. (**S/W D/E:** Design effort required using existing components beyond their original accepted specification levels or moderate development required using existing knowledge.)	Moderate engineering development is required using existing design knowledge. (**S/W D/E:** Significant development required using existing knowledge.)	Major engineering development is required using existing design knowledge. (**S/W D/E:** Major development required using existing knowledge.)	No alternative components available and/or requires new or breakthrough advance in design capability. (**S/W D/E:** No alternative components available or major development required using new knowledge.)

Note: The two category scales of Technology and Design & Engineering include some overlap since both involve the level of maturity of an item. The technology risk category primarily focuses on the hardware independent of how it will be used on any given spacecraft. The design and engineering category primarily focuses on hardware implementation partially independent of the inherent level of technological readiness (at least for design and engineering levels ≥ 2). For example, a qualified prototype star sensor may still require modification necessitated by form, fit, and function changes and specialized (i.e., radiation shielding, vibration damping, etc.) modifications that are unique to the satellite system.
Scaling assumes current Air Force qualifications procedures. Brilliant Eyes Technology/Producibility Assessment Process provided source information for Technology definitions.

Figure 9-3

Risk Category Assessment Templates

Level of	Uncertainty		
Cost-Risk Driver Category	Very Low	Low	Moderately Low
<u>**COMPLEXITY**</u>: Degrees of uncertainties due to combining parts/processes to make up the whole.	Very simple combinations and/or not very many parts/processes making up the whole.	Simple combinations; only a few parts and processes making up the whole.	Fair amount of parts/processes making up the whole with somewhat complex combinations.

	Level of	Uncertainty	
Moderate	Moderately High	High	Very High
Significant number of parts/processes making up the whole and moderate complexity in making the combinations.	Significant number of parts/processes making up the whole and some new parts required and higher complexity in making the combinations.	Significant number of parts/processes and almost totally new parts/processes and high complexity in making the combinations.	Very large number of parts/processes, totally new part/processes and very high complexity with much uncertainty in making the combinations.

Figure 9-4

Risk Category Assessment Templates

	Level of Uncertainty		
Cost-Risk Driver Category	Very Low	Low	Moderately Low
INTERACTION/DEPENDENCIES: Degrees of uncertainties due to dynamic interplay between and among external interfaces (e.g., gimball with P/L, EPS, thrusters, etc.)	Completely independent of external interfaces.	Dependent on one external interface.	Dependent on two external interfaces.

	Level of Uncertainty		
Moderate	Moderately High	High	Very High
Dependent on three external interfaces.	Dependent on four external interfaces.	Dependent on five external interfaces.	Dependent on more than five external interfaces.

Figure 9-5

Relative Risk Weighting Process for Programmatic/Technology Cost-Risk

- These templates are used by the engineers in rating the risks on element KEPPs for the risk scenarios of the WBS element. Figure 9-6 below illustrates a methodology called the Relative Risk Weighting (RRW) process that uses the risk scores generated by the risk rating process to define two ratios that are used as factors on the reference point cost estimate to derive a pessimistic and optimistic cost. Together with the reference point estimate, these two derived costs define that WBS elements triangular risk distribution.

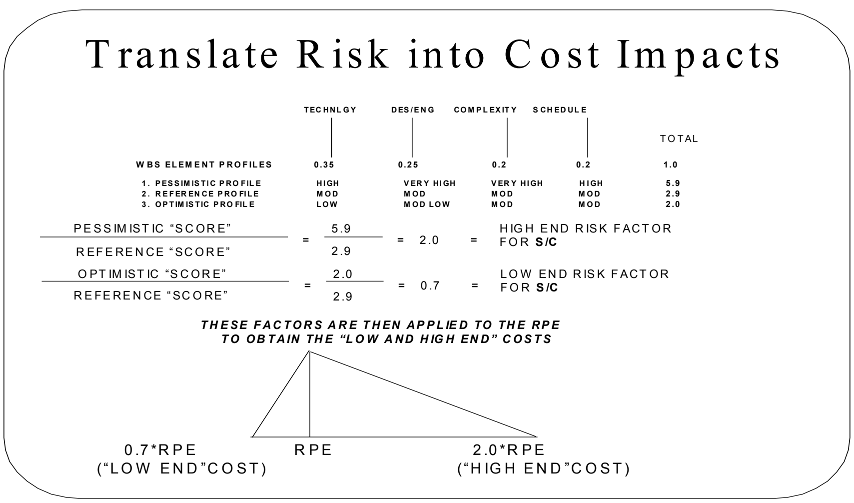

Figure 9-6

- The risk scores for each WBS element risk scenario are developed by first deriving weights for both the risk driver categories and the rating scale intensities (e.g., very high or medium low etc.). A useful technique for deriving the weights for both risk driver categories and rating scale intensities is the application of the Analytic Hierarchy Process (AHP). Weights resulting from the AHP are ratio-scale weights, that is, they have a meaningful zero point and thus have the integrity for use in all mathematical operations. The same cannot be said of ordinal or even interval level numbers.[8,9] The scores result from the sum of the products of each risk category weight and each rating scale intensity weight.

- Ratios between the pessimistic/reference scores and optimistic/reference scores are calculated and used as scalars on the reference point estimate. These ratios are credible relationships due to the equivalence of the reference profile's score to the reference point cost estimate. Both are representations of a WBS element defined in Part A of the Cost Analysis Data Requirement (CADRe), one is a cost and the other is a risk 'dimension' assessment. Having a common representation of the WBS element in two "dimensions", so to speak, and three risk assessment scores enables a translation from the risk 'dimension' into an optimistic and pessimistic cost 'dimension'.

- A variation of the RRW process involves creating pessimistic, optimistic and reference risk profiles for a CER-driving parameter (e.g., weight). The application of the resulting RRW ratios to the nominal (reference) parameter value from the CADRe reflects the parameter's potential range of values (Figure 9-7). When this range of values is entered into the CER a range of costs is produced that adds to the cost range driven by the uncertainty inherent within the CER itself. Figure 9-8 illustrates this new range.

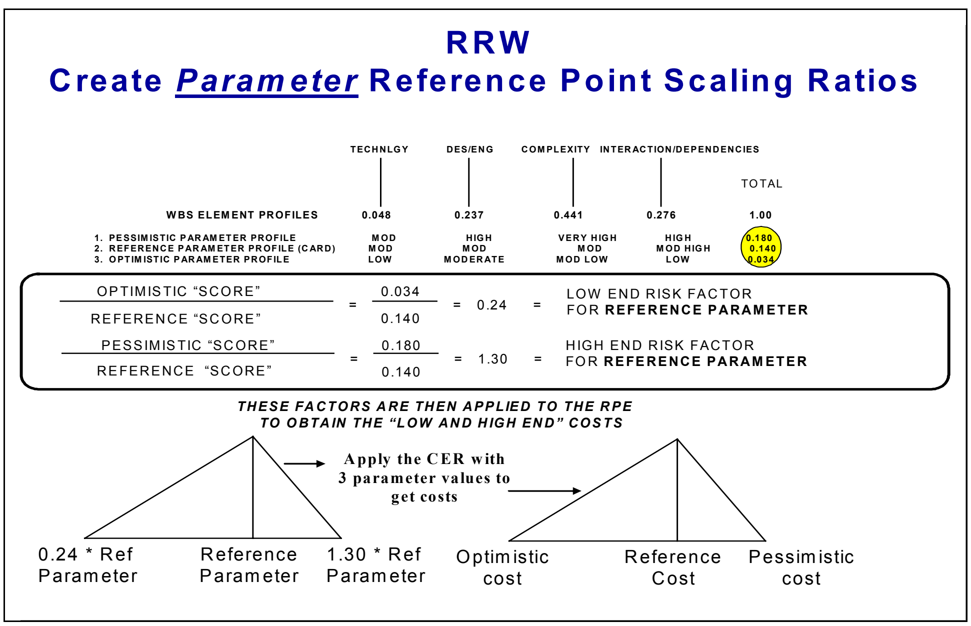

Figure 9-7

CER Results – A Cost Probability Distribution

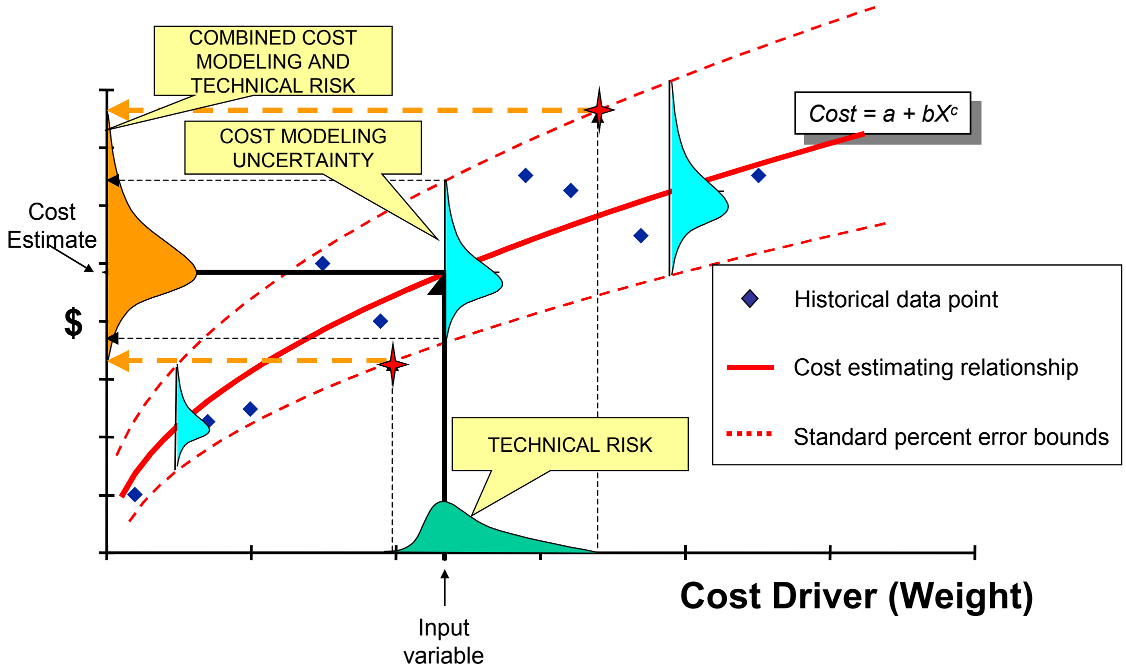

Figure 9-8

Statistical Summation

- Following the WBS element cost-risk distribution definition step above is the process of statistically summing all of the WBS element triangular distributions, including correlations, to arrive at a probabilistic range of the potential cost for the program. Figure 9-9 below illustrates the results of a statistical summation process normally performed by the cost estimators.

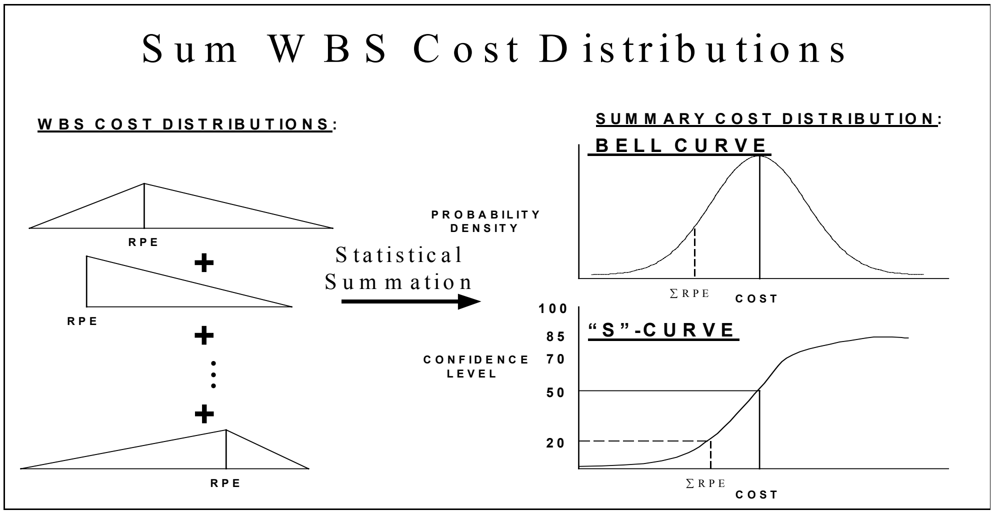

Figure 9-9

- Note that the sum of the reference point cost estimates, when triangles are skewed right (denoting more upside than downside risk), is at a relatively low level of confidence on the cumulative distribution function ("S"-curve). That is, the confidence level is approximately 20% that the total cost of the program will be at the arithmetic sum of the reference WBS element cost estimates. It is necessary to add margin budget[10] to even ensure that the program has a 50/50 chance of not overrunning at an even higher level of cost. In other words, there is very low confidence that the project can be successfully accomplished within such a low budget estimate. A higher budget estimate will have a higher confidence.

<u>*Scenarios*</u>

- Discrete KEPP risks are identified and defined during the construction of the risk scenarios: pessimistic, optimistic and reference. Each scenario has the same risks identified; it's just that in the pessimistic scenario the worst observance of them is hypothesized to occur. For example, the pessimistic scenario is a situation surrounding the development of the WBS element that assumes the realization of the worst conditions under each category of risk affecting the element in meeting the WBS performance expectations documented in the CADRe whereas the optimistic scenario is a situation surrounding the development of the WBS element that assumes the realization of the best conditions. Similarly, the reference scenario is a situation surrounding the development of the WBS element that assumes the realization of the most likely conditions. (NOTE: The reference point cost estimate in *cost* terms is equivalent to the reference scenario in *risk* terms. This equivalency underpins the argument for using the risk ratios as reference point estimate adjustment factors.)

- Each profile or scenario for each WBS element must be described in writing, detailing the specific, discrete KEPP risks to ensure clarity of understanding the situations for rating risk during the RRW process and for clearly justifying the reason for a recommended confidence level for budgeting. For example, if the WBS element being evaluated for risk is a laser amplifier/transmitter, the discrete KEPP risks may involve wave front sensing, wave generation, coatings and gratings for the mirrors, autonomous resonator alignment, bore sighting and peak electrical power generation. Furthermore, the actual situation for these discrete risks should be documented in writing and could be characterized by the following: Sensitivity levels required for wave front sensing and the ability to control it at these levels has never been demonstrated. The continuous wave generator requires power levels that have only been demonstrated in flight at 20% of the required levels. Fabrication of the coatings and gratings for the transmitter/amplifier is an established technology. Autonomous resonator alignment requires a level of precision that has never been attempted. Bore sighting is experiencing jitter in simulations and the design processes have yet to be developed. Beam stop/attenuation power switching is an established technology. Peak electrical power amplification for durations required has only been simulated in a laboratory environment.

- These discrete KEPP risks are rated in pessimistic, optimistic and reference scenarios in order to calculate relative risk scores for cost-risk triangular distribution development in the RRW process. Additionally, since the risks for each KEPP have been documented, it is possible to develop strategies for mitigating each KEPP risk and, in parallel with the RRW's probabilistic approach, produce ***discrete*** cost-risk assessments. A cost is thus estimated for handling and/or mitigating each discrete KEPP risk to determine its specific contribution to the total cost. All the discrete risk costs are summed and added to the reference cost estimate and the total is identified on the probabilistic cost assessment's "S"-curve. The associated confidence level is then compared to the 70%-80% confidence level being recommended for budgeting and the resulting reserve justified on the basis of the costs for handling and/or mitigating the discrete KEPP risks.

- There are other processes available to the cost estimator for developing cost-risk distributions other than the Relative Risk Weighting process[11,12].

6. NASA cost-risk probability distributions are justifiable and correlation levels are based on actual cost history to the maximum extent possible.

   - There are a variety of probability distribution shapes available for the cost estimator to model cost-risk. The most common are the normal distribution (especially for cost estimating risk) and the triangular for parameter input and programmatic/technology risk. An example of a normal distribution for cost estimating methodology risk is the distribution around a regression line. Its use is justified by the statistics characterizing the regression line. If some variation of the shape for the regression line distribution is to be used, other than normal, it must be justified[13].

   - The distribution commonly used for characterizing programmatic/technology risk is a triangular distribution. The triangular distribution is fairly simple to characterize since the cost-risk analyst only needs to produce three points: a reference point (sometimes called the "most likely"), a pessimistic point and an optimistic point as illustrated above in the RRW process. Both the cost estimating methodology cost-risk and the programmatic/technology cost-risk distributions must be accounted for in the final cost-risk distribution[14]. Figure 9-8 above illustrates one way for which both are accounted.

   - Correlations between WBS elements must also be accounted for in the combining cost-risk distributions. Commercial Monte Carlo simulation models such as @RISK™ and Crystal Ball™ contain the capability to apply correlation during the statistical summing of a project's WBS element cost-risk distributions. However, the cost-risk analyst must provide the correlation values. Correlation values could be statistically derived using a variety of methods. The first results from analyses between CER errors, for example, residual analysis. Another is the "Actuals-to-Predicted" method" that compares actual and predicted costs of historical systems and then infers the true total correlation coefficients of the CERs. A third method is to estimate the level of correlation based on the number of WBS elements to be summed.

   - Commercial Monte Carlo simulation software (e.g., Crystal Ball™ or @RISK™) as well as the government-owned ACEIT modeling environment also include the ability to apply statistical correlation analysis between engineering drivers, for example, between complexity, weight, power, etc. Similar methods to those described above can be used to determine these correlations.

- There are benefits and drawbacks to each approach, however. Residual analysis is difficult because the analyst needs a database of historical costs, cost drivers, CERs and CER errors. The Retro-Ice method is also difficult because the analyst needs actual cost data from several similar programs, a similar WBS structure to the one being modeled, the total error, and the use of similar cost estimating models. Estimating correlation based on the number of WBS elements is relatively easy because the analyst only needs the number of WBS items and the models' typical uncertainties but it is strongly a function of the number of correlated elements and its effect decreases with the number of correlated elements. Using the last method, adjustments can be made for the underestimating of actual correlation.

- Additional "functional" correlations can also be determined through a functional (i.e., causal) relationship, for example, between cost drivers or between cost dependent CERs (e.g., SEIT/PM). However, deriving correlation between cost drivers is hard because the analyst needs a set of Cost Engineering Tools (e.g., a Concept Design Center model, Size/Weight/Power model) to do it. However, deriving correlation between cost dependent CERs is easy since the analyst only needs cost dependent CERs (such as SEIT/PM, etc) linked to summary costs in model.

- It is important to point out that correlation is not causation (but the reverse is true). Many of the statistically high correlations derived from existing models may be in large part due to the lack of data used to determine the correlations and/or the accounting scheme used to bucket costs[15,16].

7. NASA cost-risk assessment ensures cost estimates are “likely-to-be” vice “as specified” for optimum credibility.

- The “as specified” project is the project represented by the “reference risk profile” scenario in Figure 9-6 and Figure 9-7 above. It is the project without any real consideration for estimating, parameter, programmatic/technology or correlation risks. The “likely-to-be” project is the “as specified” project plus cost impacts due to the risks. The following are well-defined steps for developing a “likely-to-be” cost estimate[17]:

- Step 1: Quantify the probability distributions describing the modeling uncertainty of all CERs, cost factors, and other estimating methods, specifically, the type of distribution (e.g., normal, triangular, lognormal, beta, etc.,) as well as the mean and variance of the distribution.

- Step 2: Define the “likely-to-be” program by identifying the relevant risks. Defining the parameter input and programmatic/technology risks is improved by implementing an independent technical assessment. Quantify the probability distributions describing the cost effects due to parameter input and programmatic/technology risks, specifically, the type of distribution (e.g., normal, triangular, lognormal, beta, etc.) as well as the mean and variance of the distribution as in Step 1 above.

- Step 3: Quantify the correlation between all WBS elements that are estimated using CERs and other methods. If unknown, assess whether NO correlation, MILD correlation, or HIGH correlation, for example: NONE: $r = 0$, MILD: $r = \pm 0.2$, HIGH: $r = \pm 0.6$. The thought to keep in mind is that correlation affects the overall cost variance.

- Step 4: Set up and run the cost estimate in a Monte Carlo framework (e.g., Crystal Ball™, @RISK™, ACEIT) or suitable analytic method (NAFCOM) that incorporates cost estimating, parameter input, programmatic/technology and correlation risk. This will result in a cumulative distribution function from which the 70th percentile can be easily identified.

- Step 5: Assess "risk dollars." "Risk dollars" is defined to be the difference between the 70th percentile and the "as specified" project cost (e.g., arithmetic sum of WBS element reference point, deterministic cost estimates) and represents the estimate of "risk dollars." Risk dollars can be allocated downward to any level of WBS using a variety of simple approaches. ACEIT and the most recent version of NAFCOM incorporate such a risk dollar allocation algorithm.

8. NASA cost-risk assessments account for all known variance sources and include provisions for uncertainty.

    - "Known" unknowns are those risks for which a probability distribution can be defined, that is, the cost estimator knows what the risks are, and can quantify their potential cost effects as a range, but cannot pinpoint exactly what point within that range represents what will eventually become the actual result. Uncertainty is those risks for which not even a probability distribution can be defined. Examples of uncertainty can be requirements growth, budget cuts, launch vehicle failures, and small engineering change orders. Even though potential cost effects due to these risks are not specifically quantifiable ahead of time, provisions for some of their cost effects can be made as a matter of organizational policy. Justification for this additional cost can be made based on records of past cost growth due to these drivers. Practically speaking, the allowed amount should be no more than 5% because it is covering only small value unknown unknown cost-risk drivers. When uncertainty cost-risk drivers result in large cost growth, additional funding will be forthcoming, however unpleasant or unfortunate the conditions of gaining that funding may be[18].

9. NASA cost-risk integrates the quantification of cost-risk and schedule risk by enlisting the support of NASA schedule and EVM analysts. NASA cost estimators should not have to become schedule risk or EVM analysts. NASA cost estimators should, in considering the cost impacts due to cost and schedule risks, confer with schedule risk and EVM analysts within the project. Specifically, they should investigate the use of adding the dimension of duration uncertainty to activities, along with traditional early start/late start - early finish/late finish, results in developing a more realistic critical path analysis (CPA)[21], that is, Risk Path Analysis (RPA). When the results of an RPA are known, the most likely longest path through the network should be used to form the basis of projecting cost impacts to the project. These impacts can form the basis for a crosscheck to a cost-risk analysis or be integrated into an existing cost-risk analysis.

10. NASA decision makers need to know[17]:

        - How much money is in the estimate to cover risk events;
        - To which WBS elements are they allocated; and,
        - The confidence level of the estimate.

    - Senior acquisition decision-makers usually desire to know a couple of things about cost estimates, for example, how much 'risk' is in the estimate. What this means is how many dollars are in the estimate to guard against 'risky' events happening and, to which WBS elements are they allocated? If the cost estimator has applied the NASA tenets of cost-risk properly, these two concerns are easily addressed. As long as discrete risk events have been identified in the risk assessment (e.g., RRW process in Tenet #5 above) and costs to cover them estimated, the cost estimator can answer the decision-maker's question. As to which WBS element they are allocated, as long as an allocation methodology has been applied as mentioned in Tenet #5 above, this question can be answered. In fact, the latest versions of NAFCOM and ACEIT contain a WBS element allocation algorithm.

- The decision makers also want to know if the budget is set at the estimate (or any other value), what is the likelihood of an overrun? This question is answerable from the results of the statistical summing of the WBS element cost-risk distributions via an examination of the resulting "S"-curve or confidence level table. For example, if the budget were set at the 70th percentile, there would be a 30% chance of an overrun.

11. NASA project cost-risk data, collected as a function of government and contractor project estimates and actuals, contract negotiations and contract data requirements descriptions (DRDs), is compiled into the One NASA Cost Estimating (ONCE) database. The cost-risk information in the ONCE database is an integration of the cost estimating information collected by the CADRe and EVM reports and includes:

   - Probabilistic risk assessments;
   - "S"-curve updates from significant contract milestones or annual updates;
   - Risk-driven cost and schedule growth documentation;
   - Externally-driven cost and schedule growth documentation;
   - Risk management plans, reports and results;
   - Probabilistic Risk Assessment plans, reports and results;
   - Medium and high risk WBS element earned value performance measurement results;
   - Documentation of all engineering technical risk assessment methodologies used in assessing cost-risk;
   - Technical parameter/characteristic data
   - Beginning-of-contract cost and schedule estimates and actuals;
   - End-of-contract cost and schedule estimates and actuals;

- Through the collection and compiling of cost-risk data, the NASA cost estimating community will be able to validate and verify cost-risk methodologies, models and results through analysis of empirical cost-risk data. This analysis can lead to improvements over time in cost-risk projections including the calculation of cost estimating calibration factors useful in source selections[22].

- Through the creation of the 11 NASA Tenets of Cost-Risk, we have developed a comprehensive process that is acceptable community-wide, that answers these questions, and that we can readily describe to senior decision-makers.

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10. Common Mistakes in Cost Risk Analysis

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Purpose and Introduction

Many cost risk analyses have had major flaws in their construction. Some of the most common examples include mathematical errors in the application of probability and statistics. Other problems include programmatic assumptions that have failed to materialize, such as: reduced testing scenarios, new ways of doing business (NWODB), and the use of commercial-off-the-shelf (COTS) technologies as a cure-all to cost growth. Improper simulation techniques, and faulty treatment of risk data and the risk results are other problems that perennially plague cost risk analyses. These troubles usually lead to narrow, or otherwise faulty cost probability distributions.

This section contains a checklist that may be used to critique cost risk analyses. Common errors are addressed one-at-a-time. Many of the examples are from recently reviewed risk estimates by hardware contractors and Systems Engineering and Technical Advisory (SETA) contractors, and contain errors that have been inadvertently briefed at conferences and at high levels within government organizations. The purpose of this section is to alert cost analysts to the most common mistakes in order to minimize their future occurrence.

This section is organized into five parts that loosely correspond to steps in the *common risk analysis flow* described in Figure 10-1. The five main topics are: defining input probability distributions; applying correlation; programmatic assumptions; statistical sampling; and interpreting risk results.

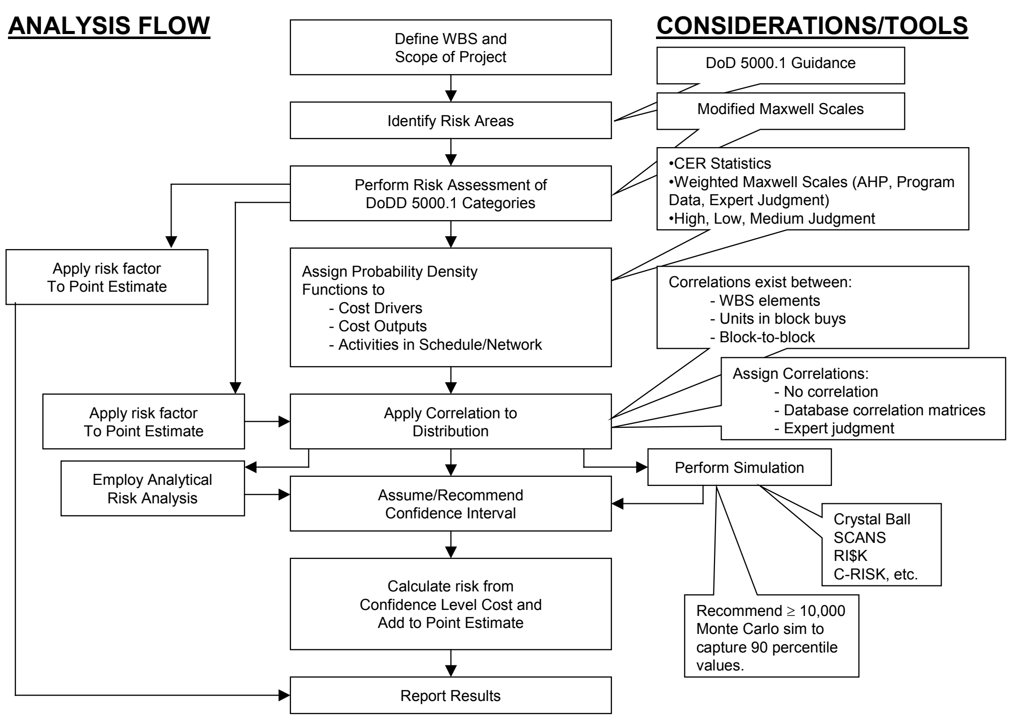

Figure 10-1 - Common Risk Analysis Flow (Courtesy of Tecolote Research, Inc.)

Input Probability Distributions

Most CERs are functions of one or more cost drivers. Under the most desirable modeling circumstances, these cost drivers are treated as random, following certain probability distributions. In this checklist, the first common error is that the input distributions are too narrow.

#1 Bad Input Distributions

Often, cost driver risk distributions do not capture the true best and worst cases. Anecdotal evidence indicates that humans tend to be optimistic creatures. When an engineer is asked for the absolute best and worst case for a cost driver, unavoidable biases often cause him/her to underestimate the extremes. Figure 10-2 shows the effect of conservative assumptions on the definition of input probability distributions.

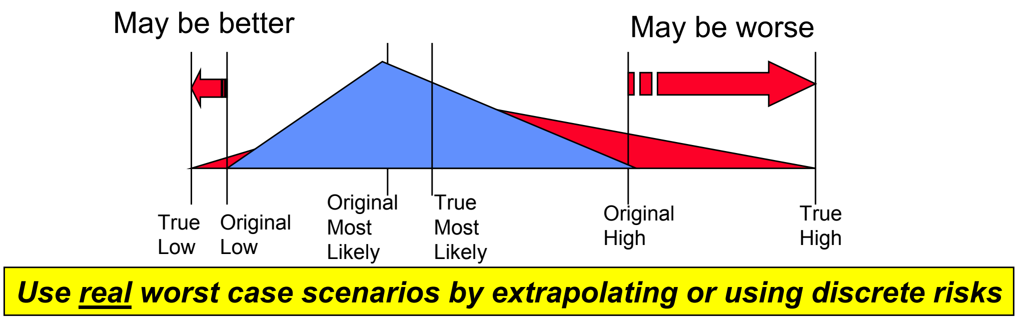

Figure 10-2 - Optimistic Assumptions in Defining Input Distributions

A key implication of this problem is that the true most likely point of the distribution may be different than the original most likely point determined under more conservative circumstances.

Another common error in defining input distributions occurs in the use of truncated endpoint descriptors as shown in Figure 10-3. This technique might be acceptable if we had a rationale such as "the historical record of one hundred programs shows one program with this maximum value and one program with this minimum value". But the question the analyst should be asking is: "Am I sure the endpoints are based on 10% - 90%, 20% - 80% or some other endpoint assumption?"

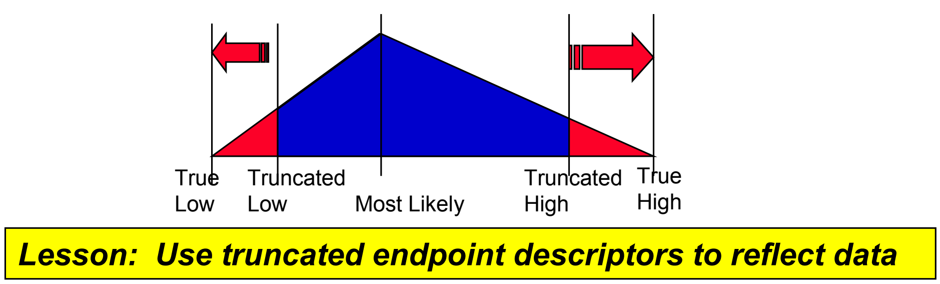

Figure 10-3 - Use of Truncated Endpoint Descriptors

The distributional characteristics, and the amount of probability found in the truncated endpoints, are not independent of the shape of the distribution. In the following example, the endpoints for a triangular distribution used as an input variable were specified incorrectly, resulting in substantial errors in the cost estimate.

Case Study No. 1: This example uses the distributions shown in Figure 10-4. The analyst desired to model a skewed triangular input distribution by basing the truncated endpoints on the mean plus or minus 1.8 standard deviations ($\mu \pm 1.8\sigma$). That is, it was assumed that both the left and right truncated endpoints would lie 1.8 standard deviations away from the mean of the triangle. It was further assumed that the area under wedge of the triangle to the left of the left truncated endpoint contained 0.0359 probability (as if it were a normal distribution). Similarly, it was assumed that the wedge to the right of the right truncated endpoint also contained 0.0359 probability. Then, the left truncated endpoint was arbitrarily set to be equal to 90% of the point estimate (0.9*PE) and the right truncated endpoint was set to be equal to 150% of the point estimate (1.5*PE). Finally, the most likely value (mode) of the triangle was assumed to be equal to the point estimate. Some obvious problems resulted from this method.

First, note that the area to the left and right of the truncated endpoints was not correctly assessed, because the probabilities mentioned in the previous paragraph apply only to the normal distribution. In addition, given the skewed nature of the triangle, there was significantly more probability in the triangle to the right of the rightmost truncated endpoint than in the area to the left of the leftmost truncated endpoint. Also, since the triangle was skewed, the assumption that the mode of the triangle was equal to the point estimate caused most of the resulting Monte Carlo observations to fall to the right of the point estimate – more so than had the mean of the triangle been set to the point estimate. The end result was that the CER evaluated using this input triangle systematically produced a distribution that was higher than expected.

The crux of this error was in the use of parameters that more correctly model a Gaussian distribution. It was inappropriate to use parameters that assume a symmetric distribution to model a skewed triangle.

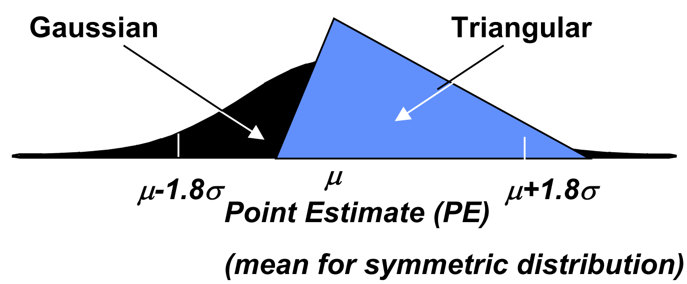

Figure 10-4 - Improper Distribution Shape - Skewness

Even so, had the analyst assumed a symmetric triangle he would still have had specification errors (Figure 10-5). While this technique would eliminate the problem of systematically overestimating the value of the CER, the fact that the percentiles of a Gaussian distribution and a triangular distribution are not equal would still result in a mis-specified CER result. This is primarily because the triangular distribution has fixed endpoints while the Gaussian distribution has infinite tails.

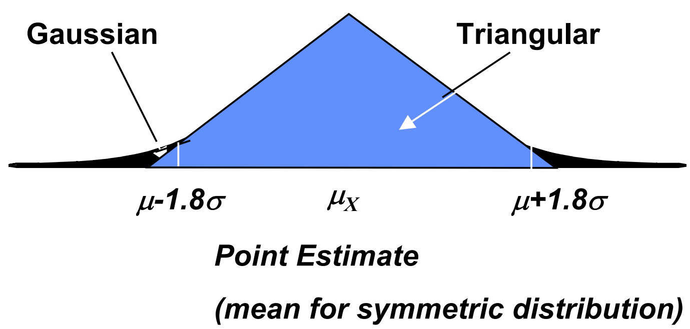

Figure 10-5 - Improper Distribution Shape - Endpoints

Suppose the modeled triangular distribution is symmetric with the low endpoint at 0.9 times the PE, the most likely at the PE and the high endpoint at 1.1times the PE, or (0.9,1.0,1.1). In this case the low point at μ-1.8σ is the 3.59 percentile point, which we set to 0.9*PE, so the extrapolated low endpoint is at 0.83*PE. The high point at μ+ 1.8σ is the 96.41 percentile point, which we set to 1.1*PE, so the extrapolated high endpoint is at 1.14*PE.

As illustrated in Table 10-1, endpoints based on extrapolating a triangular distribution will be different than endpoints extrapolated from a Gaussian distribution.

Table 10-1 - Extrapolated Values of Gaussian and Triangular Endpoints

Gaussian Distruibution				Extrapolated Triangular Distribution Endpoint (*PE)		Extrapolated Gaussian Distribution Endpoint at μ+/-3σ (*PE)	
Low Point	Percentile	High Point	Percentile	Low Endpoint	High Endpoint	Low Endpoint	High Endpoint
$\mu-1.5\ \sigma$	6.68%	$\mu+1.5\sigma$	93.3%	0.84	1.16	0.80	1.20
$\mu-1.8\sigma$	3.59%	$\mu+1.8\sigma$	96.4%	0.86	1.14	0.83	1.17
$\mu-2.1\sigma$	1.79%	$\mu+2.1\sigma$	98.2%	0.90	1.12	0.86	1.14

Therefore, one should not attempt to use parameters that are applicable to a Gaussian distribution when specifying the shape of a triangular distribution.

Lesson: Use appropriate shape statistics

#2 Point Estimate is Not Really Most Likely

The second pitfall is the oft-mistaken assumption that the point estimate resulting from the sum of a series of most likely cost estimates corresponds to the most likely value of the final cost distribution. In fact, it might be much different as described in Book [1].

For example, consider a WBS containing ten elements, each modeled by a triangular distribution with a minimum value of 0.9, a most likely value of 1.0 and a maximum value of 2.0. The triangular probability distribution that models each of these WBS elements is illustrated in Figure 10-6 below.

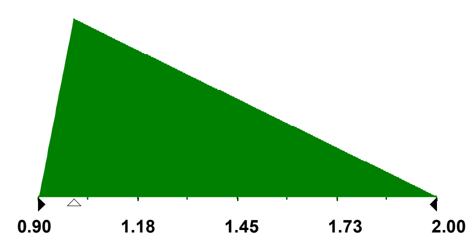

Figure 10-6 - Triangular Probability Distribution (0.9, 1.0, 2.0)

One might suppose that the sum of these ten WBS elements would result in a total cost distribution that has a most likely value of 10.0 (the sum of the ten most likely values). But that is not true. Moreover, if the WBS elements are correlated, even a little, then the difference can be even more pronounced. Figure 10-7 displays the probability distribution that results from summing these ten WBS elements. In this example, with correlation ρ = 0.2, the sum of the most likely values (10.0) actually corresponds to the 4th percentile of the distribution of the total – not the most likely value. The lesson here is that a point estimate is generally not the same as the most likely point on the total cost distribution.

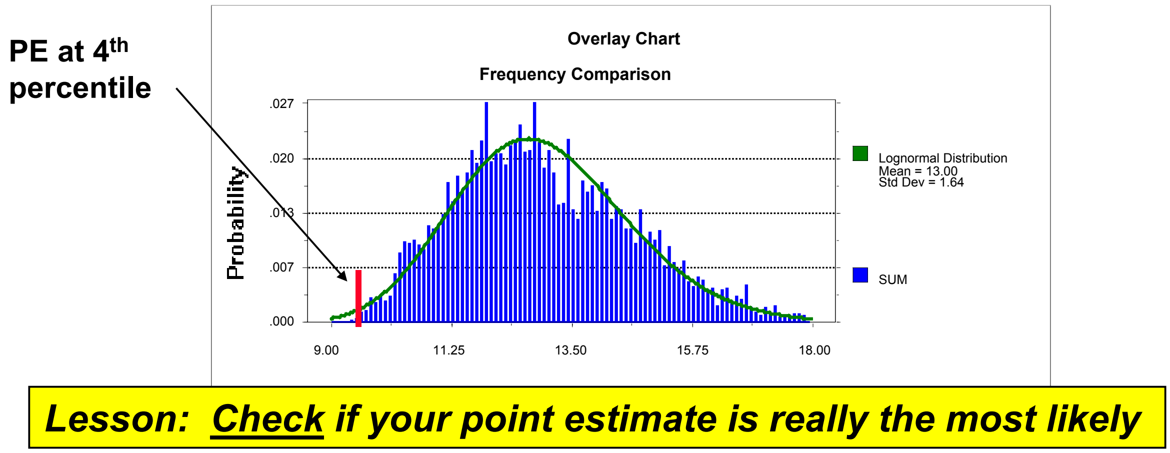

Figure 10-7 - The Point Estimate is Not Always the Mode

#3 Lack of Realistic Cost Driver Risk

The third pitfall is the lack of realistic cost driver risk. Book [2] illustrates that weight and other cost drivers tend to grow over time. Satellite weight is a well-established cost driver. The following example (Figure 10-8) shows that weight grows over time (% completion of program). Also note that weight growth is a function of the percent of New Technology, meaning the newer the technology, the greater the likelihood of weight growth.

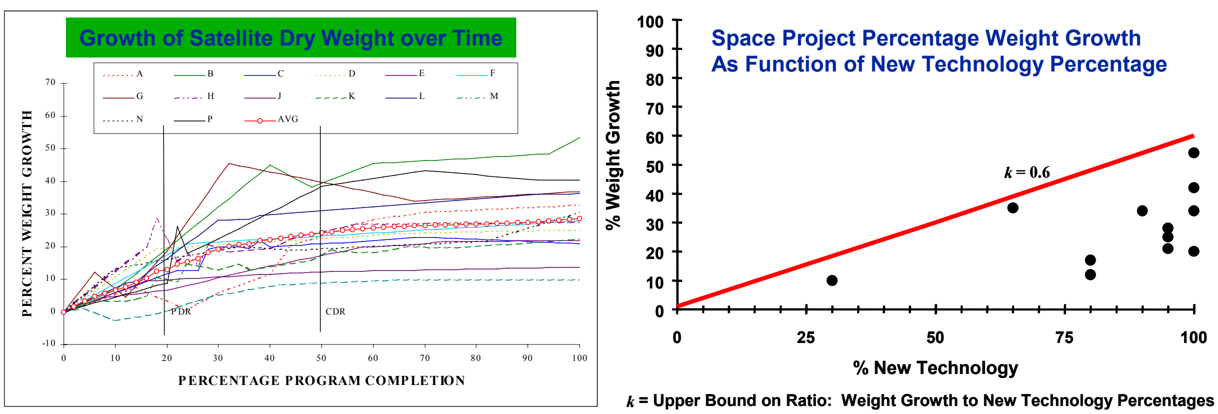

Figure 10-8 - Satellite Weight Growth

The message here is that cost drivers may have multiple dimensions of uncertainty, and that this uncertainty should be accounted for in the risk analysis as well.

Applying Correlation

In the analysis flow provided in Figure 10-1, the next step following the definition of input probability distributions is the assignment of correlation between random variables. This section deals with the problems of misspecification and neglect of this crucial step.

There are three types of correlation to consider in cost risk modeling:

1. Functional Correlation

2. Causal Correlation
3. Statistical Correlation

Each has distinct purposes and applications. The diagram shown in Figure 10-8 shows the relationships between these three types of correlations.

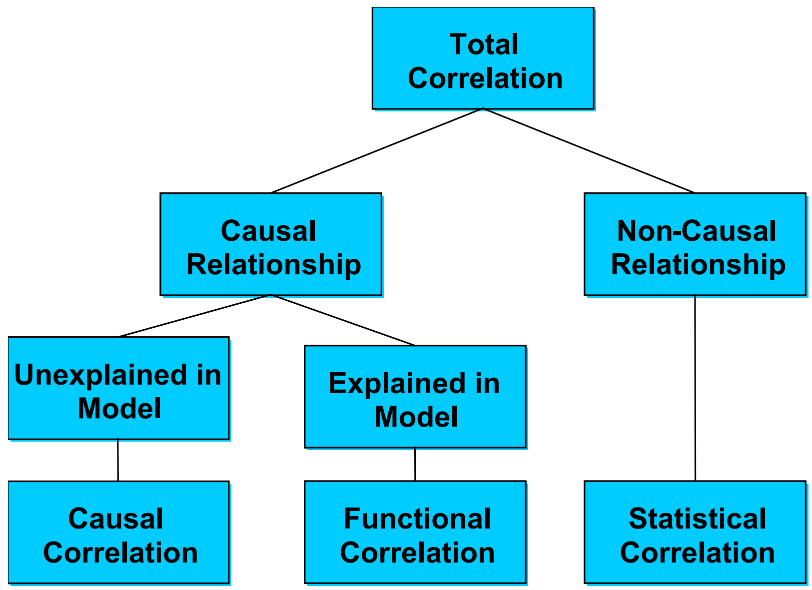

Figure 10-9 Relationships of the Types of Correlations

First, *correlation does not imply causality*, but the opposite is true. If a causal relationship exists and it is explained in the model through the use of equations relating two variables to each other, then the two variables are *functionally correlated*. If a causal relationship exists, but there is no functional relationship in the model, the two variables are *causally correlated* and some type of correlation is required for the variance of the estimate to be properly modeled. Finally, if no causal relationship exists, such as between errors in properly modeled CERs, a *statistical correlation* may exist. When we neglect correlation, we are making a modeling error. All three types of correlation may be present in your cost model, so it is imperative to understand and apply them appropriately.

The impacts of these types of correlations are different depending on the circumstances. Here are three cases where functional, causal and statistical correlation will be the dominant factor in the cost model.

Case Study No. 2: Functional Correlation Dominates

Functional correlation can be the dominant source of correlation in a probabilistic cost estimate if these conditions are met:

1. There are few WBS elements (less than 30)
2. The cost estimates of WBS elements are related to each other (such as applying a factor)
3. The cost estimates are driven by few random variables that are “reused” directly or indirectly throughout the model

In the FireSat example, the equations shown in Figure 3-1 are driven exclusively by the variance in SLOC and its by-product: the software estimate. There are few WBS elements, so the effect of statistically correlating the uncertainties of the CERs will not be a dominant factor.

Case Study No. 3: Causal Correlation Dominates

Causal correlation can also be the dominant source of correlation in a probabilistic cost estimate of these conditions are met:

1. There are few WBS elements (less than 30)
2. The cost estimating relationships are independent of each other
3. The cost estimates for WBS elements are driven by several different random variables that are not related by functions in the model

In the example shown in chapter six, Risk Analysis of a Multi-Spacecraft Satellite System, Table 6-6 shows how engineers treat causal correlation using a selection of correlation coefficients. Since there are few WBS elements in the model, and there is little functional correlation, the causal correlation values used will be the dominant source of correlation in the example estimate.

In fact, where functional correlations do not exist in our cost models, causal correlations tend to dominate when we are not accounting for the overpowering impact of summing large numbers of only slightly correlated random variables.

Case Study No. 4: Statistical Correlation Dominates

Statistical correlation will be the dominant source of correlation if these conditions are met:

1. There are many WBS elements (more than 30)
2. The WBS elements are grouped in parent WBS elements that are not causally related
3. The cost estimates for WBS elements are driven by several different random variables that are not related by functions in the model
4. There is little variance on the cost drivers
5. The cost estimating relationships are independent of each other (i.e. they are not functionally correlated) and little causal relationship is known between the variables

Two excellent examples of where statistical correlation dominates are found in Estimates-at-Completion (EAC) based on Earned Value Management (EVM) data, and Bill-of-Material (BOM) based estimates.

In the EAC example, we may be working with many WBS elements (hundreds or thousands) whose trend data is used to predict the estimate at completion. The volatility of the trend data for a particular WBS element is used to construct the PDF for that element. These volatilities can be statistically correlated, however it may be difficult to find a causal or functional relationship for them. In the EAC example there are no real “cost drivers” except the established trends and current state of completion.

In the second example, the BOM-based estimate, many WBS elements may be used. The cost drivers for this type of estimate are typically material prices and labor hours estimates that may not be causally related to each other. In this case, there is no functional correlation, and the causal correlation may prove to be negligible. Statistical correlation would certainly be the dominant form of correlation.

Improper treatment of correlation is mathematically incorrect and happens very frequently. We will now discuss how bad correlation specification leads to incorrect risk results.

#4 Bad Correlation

The fourth pitfall in cost risk analysis is the neglect of correlation between WBS elements. Ignoring correlation between WBS elements will result in artificially narrow total cost distributions. In fact, when you ignore correlation, you are not really ignoring it all. Rather, you are implicitly setting all correlation coefficients to the exact value of zero! Figure 10-10 shows the difference between the sums of random variables with and without correlation. On the left, the uncorrelated case has a narrow distribution about the mean, and on the right, the correlated case has a wider distribution about the same mean. As the number of WBS elements increases, the effect becomes even more pronounced.

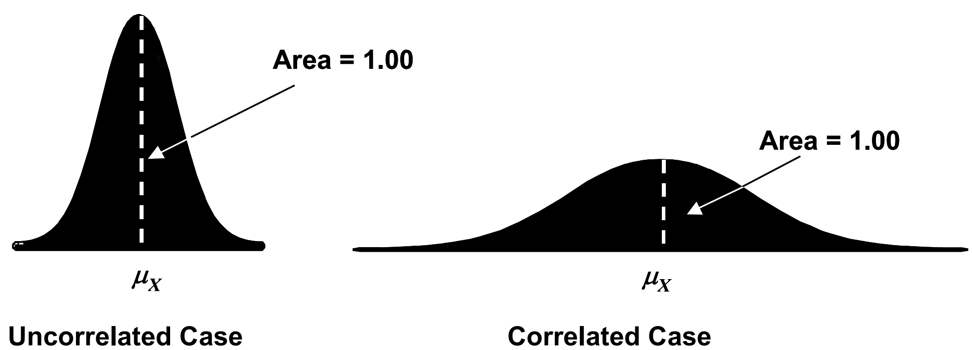

Figure 10-10 - The Effects of Correlation on Probability Distribution Shape

The amount of underestimation, or the maximum possible underestimation of the total cost variance, *k*, when correlation for all elements is assumed to be zero instead of ρ is defined in Equation 34 as:

$$k = \left(1 - \frac{1}{\sqrt{1+(n-1)\rho}}\right) * 100\% \qquad (34)$$

This effect is shown graphically in Figure 10-11. For example, with 30 WBS elements, each correlated at a nominal value of 0.2, if correlation is assumed to be zero, then the standard deviation of the total cost probability distribution will be underestimated by approximately 60%. In other words, ignoring the correlation between the WBS elements will result in a substantially narrower total cost distribution than if the WBS elements were correlated correctly. Note that the effect is more pronounced as the number of WBS elements increases, and that only a small amount of correlation makes a large difference in results. In fact, there are both positive and negative statistical correlations found in real data from different cost models examined. However the mean of all of these correlation values is a small, positive number. The trend indicates that this average correlation value becomes smaller (approaching the limit of zero) as the number of WBS elements increases. Cost models, such as NAFCOM, that have large numbers of WBS elements have a smaller average correlation than models with small numbers of WBS elements, such as SSCM. Figure 10-11 arrives at this conclusion through a simplified mathematical demonstration.

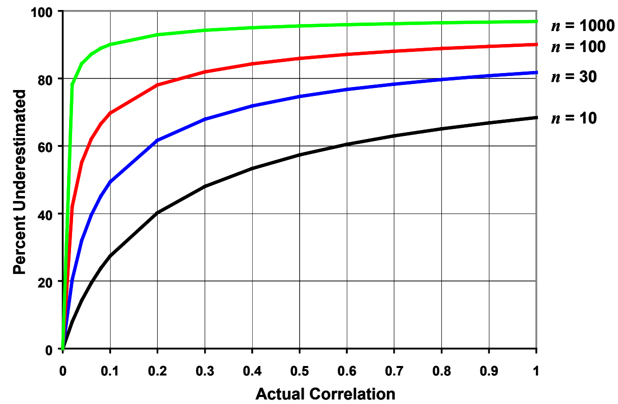

Figure 10-11 - Percent of Total Cost Sigma Underestimated by Omitting Correlation (Ref: Book [3])

Case Study No. 5: Suppose a risk analyst correctly applies probability distributions to all WBS element costs – This is good. Also assume that there are 300 cost elements (N = 300), and there are about four cost elements in each subsystem (n = 4). This means there are (N/n = 75 subsystems). If correlation is defined between all elements within a subsystem but not to the elements within other subsystems, then the proportion of the number of WBS elements that are actually correlated is N_ρ as given in Equation 35.

$$N_\rho = \frac{(N/n)[n*(n-1)]}{N*(N-1)} = \frac{(300/4)[4*3]}{300*299} = \frac{900}{89700} = 0.010033 \qquad (35)$$

In this example, only about 1% of the cost elements are correlated. If the analyst looks at the values of the correlation matrix, the correlation appears "just-off-the diagonal" of the correlation matrix – This is bad.

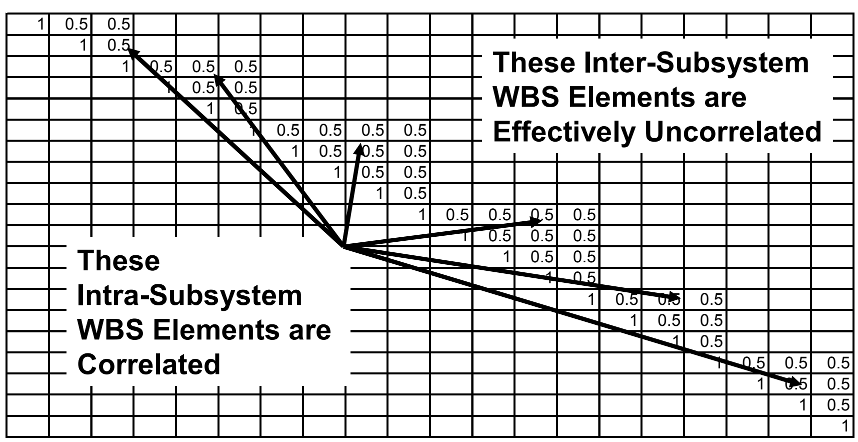

Figure 10-12 - "Just-Off-Diagonal" Correlation

Although engineers may find a difficult time justifying a *causal relationship*, it is conceivable that some nominal *statistical correlation* exists between all of these empty WBS element pairs – they are not all identically zero, and even a few percent makes a big difference with a big WBS. The mathematics suggests modest levels of correlation strongly affect total variance, but we often don't know these exact values. There are at least three solutions:

1. Perform multiple level risk analysis where correlations are known between variables being summed and at summary levels.
2. Use databases to calculate all correlation (Ref: Covert [4, 5]).
3. Guess at a level of statistical correlation (Refer to Table 2-2).

Lesson: Use some nominal level of correlation

Another problem often encountered in cost risk analysis is improper accounting of *functional correlation*. (Ref. Coleman) Some CERs use the output of other CERs as their input values. For example, a CER for SEITPM might use total hardware recurring cost as its input. An example of this type of CER is shown in the following equation.

$$SS\$_{Est,i} = a_i (X_i)^{b_i} \varepsilon_i \tag{36}$$

Where:

$SS\$_{Est,i}$ = cost of i[th] subsystem

X_i = some estimated value of cost

a_i, b_i = CER Coefficients

ε_i = Percent standard error of CER.

Whenever X_i varies, then $SS\$_{Est,i}$ varies correspondingly. Therefore, the cost estimate associated with $SS\$_{Est,i}$ is *functionally correlated* with the cost estimate associated with X_i. In circumstances such as this, it is important to construct the estimate so that the uncertainty of each estimate is quantified. In other words, during each iteration of the Monte Carlo simulation, the procedure should go as follows:

1. Obtain a random sample from the input variable cost estimate;
2. Feed this random sample into the CER;
3. Obtain a random sample from the CER evaluated at the input value given in step 2.

A common mistake in this situation is to set the input variable at some fixed value – say the mean – and then take random samples only from the CER distribution. As Figure 10-13 shows, this error causes the process to underestimate the total uncertainty. For example, suppose that the cost of Systems Engineering, Integration, Test and Program Management (SEITPM) is a function of the total hardware cost. The uncertainty obtained when both CER and input variable uncertainty are combined is wider than the uncertainty obtained through the CER only.

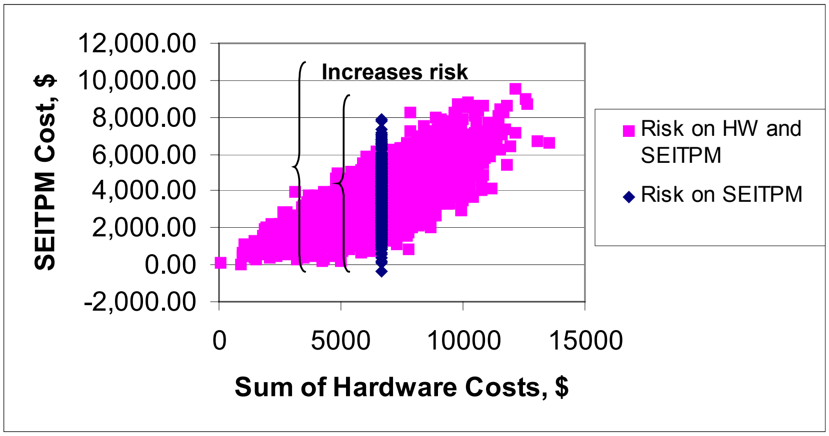

Figure 10-13 - Effect of Functional Correlation

Lesson: Account for functional correlation where possible

Programmatic Assumptions

Lack of attention to programmatic realities usually results in a poor cost risk analysis. The next two pitfalls illustrate problems that arise when scheduling problems and other discrete risks are mishandled.

#5 Cost Risk and Schedule Risk Treated Independently

The fifth pitfall in cost risk analysis results from inconsistent treatment of cost and schedule risk. Cost and schedule are not independent. However, schedule risk analysis is usually performed independently of cost risk analysis. The result is that schedule risk does not translate to corresponding cost risk, nor vice versa. The following examples illustrate this:

Example 2: Suppose a contractor estimates $140M worth of cost risk but only 6 days worth of schedule risk. Why is there such a disparity, when we know schedule is a primary cost driver? Anecdotal evidence indicates that schedule risk is calculated even more poorly than cost risk because key dependencies and probability assumptions are usually not modeled correctly, or at all, in the schedule realm.

In this case, it is obvious that cost is not tied to resource/schedule realities. If one were to add 20% to cost, would there be 20% more hours spent in same amount of time? This is similar to having nine women produce one baby, when in fact we know (or should know) that the schedule (nine months) and resources (one woman) are predetermined realities.

Example 3: Here we examine the question, "Given a change in programmatics, is it more appropriate to change the magnitude of the cost estimate in order to adhere to a fixed schedule, or to slip the schedule in order to ‘fit’ the updated cost estimate?" Suppose a program manager is overseeing a program whose base year cost estimate is $1B (BY00) with 17% estimated cost risk. Suppose further that the program’s outlay schedule is phased using the phasing profile given in Table 10-2, and that the inflation rate is assumed to be 3% annually.

- Table 10-2 Example Phasing Profile

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Phasing	0.061	0.152	0.158	0.137	0.116	0.092	0.071	0.039	0.068	0.025	0.022	0.020	0.018	0.016	0.004

Given these assumptions, it is possible to calculate the program cost as $1.14B (TY$). Now suppose that the preliminary design review (PDR) is in 2002 and that the 17% base year slip is equivalent to a one-year slip after PDR. Schedule slips commonly occur between PDR and CDR (Ref: IDA [6]). The question is: Should the program manager keep the same phasing profile or slip the schedule?

If he keeps the same schedule and phasing, then the magnitude of the TY$ must necessarily increase. A key assumption is that the resources are available to support packing more work into the same amount of time. On the other hand, if he decides to slip the schedule, then this results in increased TY$ due to both increased work and inflation as well as an increase in schedule duration. This may be the case if additional resources are not scalable or the program manager had to go “back to the drawing board”.

Figure 10-14 illustrates the effects of both scenarios. Note the slipped schedule case has higher magnitude TY$ impact than the case where the program manager merely increased the amount of resources.

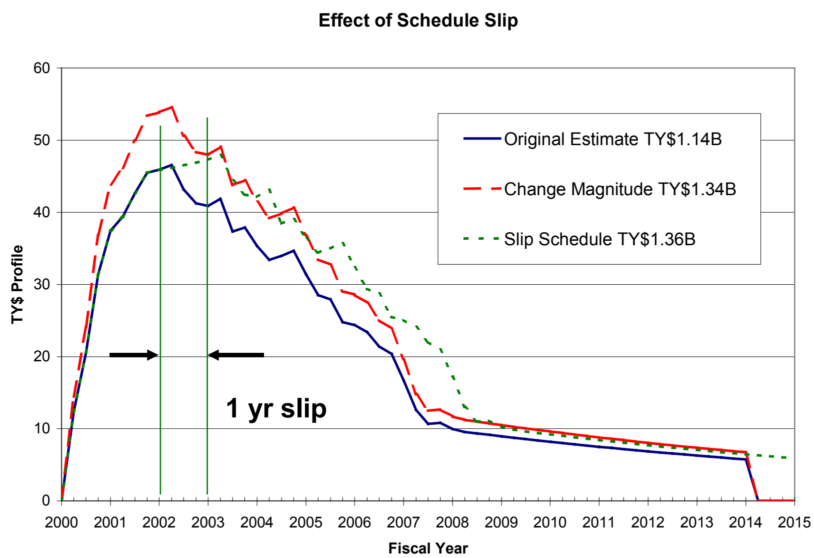

Figure 10-14 - Effect of Schedule Slip

If resources are not scalable and if redesign may need to be done then the program manager should slip the schedule by changing the phasing profile. This can be derived from the BY$ risk. The lesson here is that we should use schedule slips based on cost risk.

Lesson: Use schedule slips based on cost risk

#6 Missing Risks

The sixth pitfall in cost risk analysis is to ignore the usual, predictable risks. Failure to identify these common risks inevitably leads to tighter (i.e., less realistic) uncertainty distributions, and lower overall cost estimates. Figure 10-15 shows the spectrum of typical program risks.

- State-of-the-Art-Advance (Technology Readiness)
- Technical Risk Sources
  - Physical properties
  - Material Properties
  - Radiation Properties (emission and reception)
- Material Availability Risks
- Testing / Modeling Risks
- Integration / Interface Risks
- Program Personnel
- Safety Risks
- Software Design Risks
- Security Risks
- Critical failure modes
- Energy / Environmental Risks
- Schedule problems and delays
- Inadequate cost estimates
  - Process (need to assess contractor's assumptions)
  - Models
- "New Ways of Doing Business"
- Inflation
- Systems Engineering
- Cost Improvement Curve Assumptions

Amount of cost risk depends on the Basis of the Estimate

Historical cost data available

Figure 10-15 - Spectrum of Program Risks

For example, inflation risk is typically ignored in cost risk analyses. However, it is possible to model inflation risk based on history. Consider Figure 10-16, where inflation uncertainty based on DoD statistics since 1960 is modeled. Note the expected effect of inflation risk over time is the growth of uncertainty as time increases.

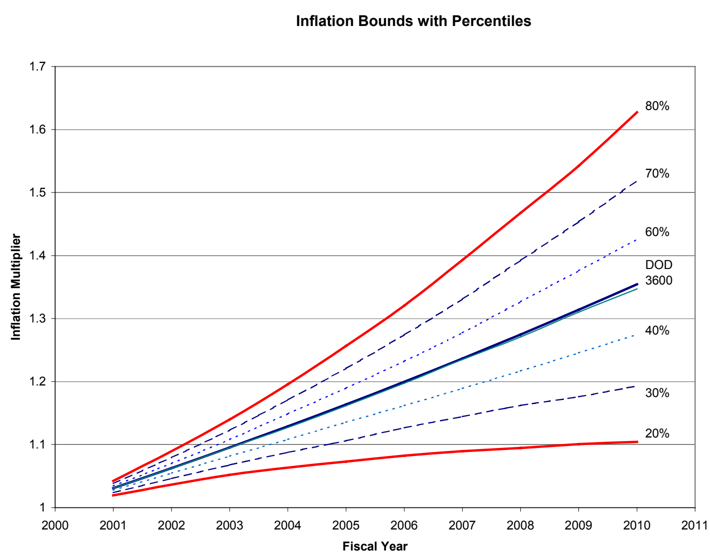

Figure 10-16 - Inflation Risk

The lesson here is that there are many areas of risk that can easily be incorporated in cost estimates. All reasonably predictable risks should be included in the cost modeling process.

Statistical Sampling (Number of Monte Carlo Trials)

An often-debated subject is the determination of the number of statistical trials to perform in a Monte Carlo simulation. The next discussion centers on how to choose the right number of trials.

#7 Over Sampling or Under Sampling

The seventh pitfall in cost risk analysis is the use of too few or too many samples in Monte Carlo simulations. Too few samples could lead to incorrect results. Too many samples may drive the risk process to be a time-intensive endeavor. So, How many Monte Carlo Trials are sufficient? There are mathematical ways of approaching this problem, but in most cases, 100 trials are probably not sufficient, and 100,000 trials are probably overkill. You will get different answers using both of these extremes. Consider the sensitivity of an output distribution to the number of trials as shown in the following example.

Example 4: Suppose we desire to sum 15 triangular distributions as shown in Figure 10-17 with parameters L=0.9, M=1.1, and H=1.8. Suppose also that each distribution is correlated with $\rho = 0.2$. We will sum these distributions using Monte Carlo simulation with a variety of numbers of iterations, deriving the summary statistics and determining the fit of the resulting distribution of the sum.

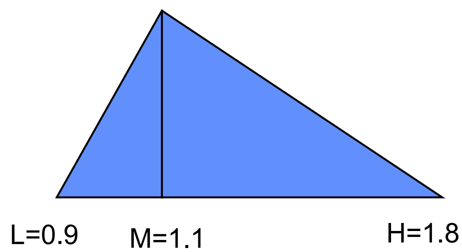

Figure 10-17 - Example Input Distribution

Ten different simulations were run with the number of trials varying from 100 to 100,000 as shown below in Table 10-3. Note that with 5000 trials, the solution seems to have settled with the following statistics:

4. Distribution shape = Gamma
5. Mean = 19.00
6. Standard Deviation (σ) at 99.3% of 100000 trials
7. Coefficient of Variation (CoV=σ/μ) at 7.6%
8. Mean Standard Error = 0.5%

Table 10-3 - Results of Monte Carlo Trials Experiment

Trials	Distribution	Duration	Mean	Median	Std. Dev.	Variance	Skewness	Kurtosis	CoV	Min	Max	Width	MSE
100	Gamma	1	18.95	18.89	1.406	1.978	0.346	2.724	0.074	15.889	22.673	6.784	0.141
200	Gamma	2	19.05	18.94	1.424	2.027	0.374	3.179	0.075	15.889	23.603	7.714	0.101
500	Lognormal	5	19.08	19.00	1.451	2.105	0.210	2.909	0.076	15.616	23.603	7.987	0.065
1000	Lognormal	10	19.03	18.94	1.447	2.093	0.216	2.783	0.076	15.616	23.603	7.987	0.046
2000	Weibull	20	19.01	18.92	1.437	2.065	0.311	2.997	0.076	15.503	24.881	9.378	0.032
5000	Gamma	50	19.00	18.92	1.430	2.046	0.268	2.923	0.075	14.810	24.881	10.070	0.020
10000	Gamma	100	19.00	18.94	1.434	2.056	0.266	2.928	0.075	14.810	24.881	10.070	0.014
20000	Gamma	200	19.00	18.94	1.440	2.073	0.250	2.880	0.076	14.733	24.881	10.147	0.010
50000	Gamma	500	19.00	18.94	1.440	2.074	0.242	2.842	0.076	14.733	24.881	10.147	0.006
100000	Gamma	1000	19.00	18.93	1.439	2.072	0.253	2.856	0.076	14.733	25.538	10.805	0.005

Lesson: There is a sufficient number of trials given estimate accuracy

So, for this particular example, it appears that 5000 iterations appears to be sufficient. However, the correct number of iterations varies from estimate to estimate, and is a function of circumstances such as: number of WBS items; amount of functional correlation; nature of input distributions and CER distributions; as well as many other variables too numerous to mention. The lesson here is that there is a minimum threshold of the number of iterations necessary to achieve realism, and that number may be different from estimate to estimate.

Interpreting Risk Results

The last part of the analysis flow provided in Figure 10-1 is the proper interpretation of risk analysis results. This is just as important as any of the other steps and is mishandled just as frequently as other areas of cost risk analysis.

#8 Adding Percentiles

The eighth pitfall occurs when cost analysts attempt to add percentiles resulting from Monte Carlo simulations. Under most circumstances, one cannot add like percentiles from various probability distributions and expect the sum to be equal to the same percentile in the probability distribution of the total. That is, suppose one desires to know the 80th percentile of the total cost distribution. If one were to add the 80th percentiles of the underlying WBS elements, the resulting number would not, in general, be equal to the 80th percentile of the total cost distribution. There are a few circumstances in which the sum of the percentiles is equal to the corresponding percentile of the sum, but these circumstances are rare. Two obvious cases when this would happen are when (1) all underlying distributions are symmetric and you are adding the 50th percentiles; and (2) all underlying distributions are perfectly correlated ($\rho = 1.0$), in which case the sum of any percentile is equal to the percentile of the sum. However, these cases are not usually encountered in cost estimation. Consider the following example that looks at the problem of adding percentile outputs from a typical Monte Carlo simulation.

Example 5: In this example, ten triangular probability distributions with parameters L=0.9, M=1.0, and H=2.0, all with inter-WBS correlations $\rho = 0.2$ are summed. The output of this summation is shown in Table 10-4.

Table 10-4 - Errors in Summing Percentiles

Percentiles	20%	40%	50%	60%	80%	Mean
WBS 01	1.06	1.19	1.26	1.34	1.53	1.30
WBS 02	1.06	1.19	1.26	1.34	1.53	1.30
WBS 03	1.06	1.19	1.26	1.34	1.53	1.30
WBS 04	1.06	1.19	1.26	1.34	1.53	1.30
WBS 05	1.06	1.19	1.26	1.34	1.53	1.30
WBS 06	1.06	1.19	1.26	1.34	1.53	1.30
WBS 07	1.06	1.19	1.26	1.34	1.53	1.30
WBS 08	1.06	1.19	1.26	1.34	1.53	1.30
WBS 09	1.06	1.19	1.26	1.34	1.53	1.30
WBS 10	1.06	1.19	1.26	1.34	1.53	1.30
MC SUM	11.89	12.58	12.98	13.26	14.09	13.00
Arith SUM	10.62	11.88	12.58	13.37	15.31	13.00
Delta	-1.27	-0.70	-0.40	0.11	1.22	0.00

Monte Carlo generated sum

Notice that none of the sums correspond to the percentile of the total. For example, the sum of the 80th percentiles is 15.31, while the 80th percentile of the summed distribution is 14.09. Notice also, however, that the means *do* add correctly. The mean is unaffected, because the mean of the sum is equal to the sum of the means in all circumstances. But this phenomenon does not extend to other locations in any of the distributions. The lesson here is: "Do not sum percentiles, but it is permissible to sum means."

#9 No Risk Mitigation in Estimate

The ninth pitfall in cost risk analysis is the lack of risk mitigation in cost risk estimates. Often there is a budget for risk mitigation schemes, but after the cost risk has been calculated the money or hours that should be allocated to these plans is not budgeted. The problem of how to budget risk is difficult, but we know from experience that we need to fund risk mitigation plans fully until the risk is retired. We should move a percent of risk dollars and schedule margin into the system definition phase (NR) where we typically see the largest cost growth and also include cost and schedule margin for rework, previously undefined testing, and outsourcing events. After the much-touted new ways of doing business (NWODB) initiatives, we are finding that the "old ways of doing business", namely detailed design, reviews and testing may prevail in the end. Cutting back on testing time and procedures may not be wise, so cost and schedule need to have sufficient margins if cost cutting or procedure cutting measures are proposed in the original plans and cost estimates.

Lesson: Risk needs to be phased properly

#10 Interpreting Cost Risk Analysis

The last pitfall in cost risk analysis is the percentile at which to report the estimate. Should we budget at the 50^{th}, 70^{th} or 80^{th} percentile? If you made common mistakes (#1 through #9) then budgeting at the 80^{th} percentile may account for some of the error. Perhaps it will not. If you were careful not to make common errors in your risk analysis, however, budget at the 50^{th} percentile, or the mean. Budgeting at the 50th percentile means there is an equal probability of your estimate being higher or lower than actual cost. Budgeting at the mean, or expected value is another recommended approach. Budgeting at one of these points prevents over-funding of particular programs at the expense of others. In any case, seek some peer review and get an assessment of your risk analysis before completing your risk analysis and reporting results.

Conclusion

In conclusion, we have presented ten common problems with cost risk analyses. We can always find more things wrong if we look hard enough. After all, we are not perfect. We should also cross-check our estimates and risk results using Peer review and with actual data, if possible.

We need to look at every assumption in our estimate to ensure the risk analysis makes sense. First, use real worst-case scenarios by using truncated endpoint descriptors to reflect data or by using discrete risks. Also, we should examine the use of discrete risks because many “what ifs” help explain risk better, and we should use realistic cost driver risks. When defining risk distributions, use appropriate shape statistics and check if your point estimate is really the most likely. When using a probabilistic risk method, include correlation, both statistical and functional, where appropriate. Remember that the overall summed coefficient of variation (COV) shouldn’t be much better than the COV of the constituent CERs.

When modeling, we should use schedule slips based on cost risk and program realities. If a Monte Carlo method is used for modeling, ensure that you use an appropriate number of Monte Carlo trials. Finally, don’t make-up for bad risk analysis by budgeting at a higher percentile such as the 80th%.

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11. Elicitation of Subjective Probability Distributions in Cost Risk Analysis

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Introduction

It has become a truism of cost estimation that there is no "right" cost estimate; for any particular estimate, there is some inherent risk, for example, the possibility that the actual cost will exceed that estimate by various amounts. A cost estimate is actually a forecast, with inherent uncertainties due to changes in requirements, technology, economic environment, political considerations, and a multitude of other factors. The response has been to advocate that cost estimates be expressed not as a single point estimate but as a range of "likely" costs. Starting with Dienemann and Sobel in the 1960s through researchers such as Book and Garvey today, one major approach to cost risk has been probabilistic, i.e. expressing the uncertainty in a cost estimate as a probability distribution and using that distribution to compute quantities such as expected cost, most likely cost, budget levels with various probabilities of overrun, etc. This approach is advocated in a variety of publications, such as NASA's *Cost Estimating Handbook* (NASA, 2004), the *DOD Acquisition Risk Handbook* (DOD, 2003), a book length treatment by Paul Garvey (Garvey, 2000), and numerous articles and tutorials by other prominent workers in the field.[14]

The early papers simply assumed that such a distribution had already been constructed, presumably by using historical data with an appropriate statistical method, and proceeded to explicate what could be done with the distribution to inform decision makers, but it soon became evident that the actual construction of such a probability distribution for cost was not a trivial exercise. In a review of methodology, Fisher (Fisher, 1962) praised the analytical rigor of the methodology, but noted that it was difficult to get the distributions. However, he expressed optimism that techniques could be found to get the underlying distributions.

The use of *cost-estimating relationships* (CERs), which are usually regression equations based on historical data, provide a measure of uncertainty of a cost estimate as a confidence interval for prediction. However, that estimate assumes that the values of the independent variables of the CER are known exactly, which is not true for a project in the early stages of planning. Further, in some cases historical data is not available to construct credible CERs; this arises with radical new technology or new manufacturing processes (see, e.g. Kitchenham et.al., 2002).

To get probability distributions for values of independent variables in CERs or for the characteristics of new and untried technologies, the proposal has often been made to tap the resources of expert judgment, such as that possessed by engineers, managers, and other knowledgeable people, and construct *subjective* probability distributions to represent uncertainty where data is not available or is considered not relevant. This process is called *elicitation* in the wider literature of decision analysis, and is known to be difficult to do and can be subject to numerous biases. However, its potential utility and the fact that it is widely advocated in cost risk analysis requires that we understand how to do it well in order to have credible risk analyses.[15]

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[14] This chapter focuses primarily on quantifying cost uncertainty parametrically by eliciting formal subjective probability distributions. There are other approaches to describing and reasoning with uncertainty, which take advantage of expert opinion, but do not require formal probability distributions, although such distributions can be used. Two notable examples are the Delphi method, developed at RAND in the 1950s and extended and widely applied since then to summarize views of expert panels (see, e.g. Adler and Ziglio, 1995 for a recent reference), and assumption-based planning, which aims to relate potential paths of a project to specific sets of alternative assumptions (Dewar, 2002).

[15] Some authors argue that expert opinion should be used very sparingly, if at all (see, e.g. Conrow, 2003).

This chapter is based on a selective review of the literature of elicitation, both in the cost risk field and in other areas where elicitation has been a topic of research, primarily statistics and psychology. Because of a lack of empirical work in elicitation, especially in cost risk, the author also interviewed a number of senior people in the cost risk community who gave insight into the practices of the field.

Elicitation

Elicitation in cost risk analysis focuses on obtaining a subjective cost probability distribution directly or (more commonly) eliciting a subjective probability distribution for some project characteristic that is a cost driver, such as weight, power usage, or development schedule. Since these variables are used as independent cost drivers in CERs, the subjective distributions can be used to get a predictive distribution for cost that includes uncertainties in the inputs as well as the estimating relationship, and the resulting distributions for subsystems can be added with other cost distributions via Monte Carlo simulation or analytic methods to get an overall cost probability distribution for the entire project (Garvey, 2000, Arena et al, forthcoming).

The actual practice of elicitation for cost risk purposes is somewhat hard to determine, because there is little information in the professional literature, other than tutorials, that actually explains how elicitation should be done. The tutorials generally recommend asking an expert for the maximum, minimum, and most likely values of the quantity whose distribution is being elicited, and then recommend fitting a triangle distribution to the three numbers (Morgan and Henrion, 1990, or Garvey, 2000). In some special cases, it may be recommended to ask an expert for percentiles of the distribution and then to fit a normal, a log normal, or a beta distribution to these quantities, but specific information on how these procedures should be done, how they should be checked, and how they perform with respect to known biases in elicitation is largely absent in the cost risk literature.[16] However, elicitation has been treated in several other areas of decision analysis, so this literature can be surveyed to evaluate elicitation practices in cost risk analysis.

Elicitation in Decision Analysis

Elicitation as an area of research arose out of several developments in the 1950s and 1960s. The first was a renewed interest in Bayesian statistics whose practitioners argued, against the prevailing frequentist school, that probability should reflect a subjective state of knowledge, with a rational person using Bayes rule to modify an initial state of knowledge (the prior probability distribution) with data to form an updated probability distribution (a posterior probability distribution). Bayesian statistics therefore requires two elements: *eliciting* the prior distribution and then performing the mathematical calculations required to apply Bayes theorem. Advocates such as Savage (Savage, 1954) and Lindley (Lindley, 1983) argued strongly that this was the only way to do statistical inference and arrayed an enormous amount of intellectual activity to show that the frequentist approach could lead to absurd decisions even in relatively simple cases.

The parallel development of general risk analysis, with its need to quantify probabilities of hazardous events, was also an impetus to developing many of the more sophisticated elicitation methods. For example, a major study on nuclear reactor safety used extensive elicitation and culminated in a guide to elicitation practices (Wheeler et. al., 1989). These methods were later used and extended in the area of environmental risks, which required quantifying the prevalence of environmental hazards, the exposures of various populations, and the effects of those exposures on individuals' health, often with scant data. For a detailed review and example see Henrion and Morgan, 1990.

As a result of this interest, a number of psychologists had begun to study the general topic of human decision making under uncertainty. In a typical experiment, subjects would be asked questions whose answers were unknown to them, and then asked to quantify their uncertainty about the answer they gave. Usually this uncertainty was expressed in terms of a probability distribution by the researchers, although the questions asked of the subject may or may not have used probabilistic terminology. The results of these

[16] For example, Lurie, et.al., 1993, emphasizes the mathematical and probability aspects of cost risk analysis, and assume that the distributions have already been determined.

experiments were distressing: by and large, human beings were subject to a number of biases, which distorted their judgment about the uncertainty of their knowledge. The most commonly listed biases encountered were[17]

- Availability: the tendency to overestimate the probability of events that are easy to recall

- Representativeness: judging probability of events by focusing on characteristics (possibly irrelevant) in which they resemble other events.

- Anchoring and adjustment: an initial assessment of a value biases the final assessment toward that value by constraining subsequent adjustment of the assessment in the light of new evidence.

- Overconfidence: underestimation of uncertainty about a quantity.

However, there were a number of criticisms of this research that are relevant for elicitation practice. First, the vast majority of the experiments were done with subjects (typically university students) who were not experts in the areas in which they were being questioned,[18] and who were in general not familiar with probability concepts. In several attempts to carefully study the elicitation of truly *expert* opinion, the results were mixed. Some researchers found that experts were not subject to one or more of the common biases.[19] Others found that experts' performance worsened when they were then asked almanac questions in areas in which they were not expert (Mullin, 1986). A further criticism by Edwards (Edwards, 1975) noted that the testing situation itself was very artificial, since it typically denied the experimental subjects, whether novice or expert, the use of reference materials, computational devices, or any intellectual tools at all .[20] There were also questions about the desirability of decomposing elicitation tasks; with some authors' results showing it improved performance, others indicating some key problems with the decomposition, and later reviewers equivocating (Morgan and Henrion, 1990).

In the end, the relevance of the psychological research for expert elicitation was in some doubt. Oddly enough, there was little empirical research that attempted to tie the research to elicitation practice, a fact noted by several researchers who attempted to synthesize the literature (Morgan and Henrion, 1990, Meyer and Booker, 2001, and Garthwaite et. al., 2004). For example, it is not clear that the research on biases led to many specific techniques that would counteract any of the biases. And although some suggestions were made, such as having an elicitor ask the subject to explicitly think of reasons why their initial estimates might not be correct to counter overoptimism and to counter anchoring, by asking for range extremes first, instead of a most likely value. However, there was little empirical evidence documenting the effect of these modifications, as plausible as they seemed.

Development and interest in these issues lagged in the statistical field up until the mid-1990s because Bayesian mathematical computations were intractable except in certain special cases, leading to Bayesian statisticians confining their attention to simpler problems and not dealing with elicitation,[21] although in general risk analysis application of these methods persisted. However, in the late 1980s a new computational tool, Markov Chain Monte Carlo simulation, allowed Bayesian statisticians to use the rapid increase of computational power to accurately estimate posterior distributions for essentially arbitrary prior

[17] The canonical list is in (Kahneman et.al., 1982), but variants are given in (Mullin, 1986), (Hogarth, 1987), (Morgan and Henrion, 1990), (Wolfson, 1995), and (Garthwaite et.al., 2004).
[18] The questions used in these studies were often simple factual questions such as the distance between two cities, and were often termed "almanac" questions.
[19] Weather forecasters are particularly good (see Morgan and Henrion, 1990, p. 130).
[20] Note that the elicitations described in Mullin and in Morgan and Henrion did in fact allow the subjects complete access to these materials.
[21] There were exceptions, see, e.g. Kadane, 1996.

distributions. This in turn sparked a surge of papers in the late 1990s reviving issues of practical elicitation (Chaloner, 1996, Wolfson, 1995, Kadane and Wolfson, 1998, O'Hagan, 1998, Meyer and Booker, 2001).

Elicitation in Cost Risk Analysis

How do the elicitation procedures used in the cost risk community compare with the methodologies and limited empirical studies in the psychological and statistical literature? As noted previously, the initial literature of cost risk analysis displayed little interest in the practicalities of elicitation, even while routinely recommending elicitation of expert judgment where data was scarce or where historical data might be irrelevant. In addition, the open cost analysis literature has had few articles on techniques. Perhaps most surprising, a review shows little overlap in the literatures of elicitation in cost risk analysis with that of elicitation in other fields such as general risk analysis, statistics and psychology. In the mid-1980s Wallenius pointed out that a key review paper on the current state of cost estimation had no overlap in citations with the book by Kahneman et.al (Wallenius, 1985, referring to (Kahneman et.al., 1982) and (McNichols, 1984)). This has largely continued until today: in general, when cost analysis authors do touch on elicitation and reference any sources outside the cost analysis field, it is usually a recent major review of uncertainty and they refer readers to that for more detail on how to do an elicitation. Up to the early 1990s, the preferred reference was Kahneman et. al., which actually did not provide a good set of practical guidelines to elicitation, as much as it documented the biases to which elicitors (particularly naive ones) were subject. Since then, the preferred reference has been the book by Morgan and Henrion, which does in fact provide considerable guidance on procedure.

However, as with the general elicitation literature, there is little discussion in the open cost risk literature of the elicitation processes actually used. In most reports elicitation is given short shrift compared with probability calculations and final results.

But even the sketchy details given, supplemented by the author's informal conversations with a variety of practitioners, indicates that there are important gaps between practice in the cost analysis field and that recommended by Morgan and Henrion and Meyer and Booker. The latter authors devote much time and energy to selecting experts, preparing initial written materials for the experts on the problem and its context, and doing the elicitation. At least some of the procedures are designed to counteract the classic elicitation biases enumerated above and in all cases care is given to feeding back the results of the elicitation to the experts in a form which allows the experts to see the implications of their judgments and perhaps revise the quantification of their beliefs. Perhaps most important, these authors recommend carefully documenting the elicitation procedures and results.

In addition, elicitation practices in cost risk analysis are very diverse, with little standardization, even in areas such as space where one might expect a convergence of practice. Individual organizations also vary greatly. However, based on the interviews done by the author, there are a number of common worrisome issues in current elicitation practice in the cost risk field:

- Experts selected for elicitation should have technical expertise in order to understand technological issues, management experience to appreciate the organizational challenges that can arise, and above all independent of the project under review. However, in practice selection of experts is often a matter of convenience in terms of access. In many cases the only experts easily available are engineers from the program office, who provided the initial technical and/or cost estimates; they tend to stick to a very narrow distribution around their initial estimate.

- Elicitation is often rushed due to time constraints of the experts and time and financial constraints on the elicitors. This is particularly true in some of the government cost analysis shops where staff cuts have been severe. In many cases the elicitation is done by mail or web form with little interaction with the subject.

- Elicitation methodologies are largely ad hoc and are rarely justified by their performance (in bias reduction, for example). They are virtually never based on elicitation references outside the cost risk field.

- Feedback is rarely given to the expert about the implications of the elicitation, even in terms of historical data.

- There is little or no documentation prepared or retained about the process, forms used, etc. It is especially hard to go back to finished projects and get historical information about the elicitations that were done.

- As a consequence of the last point, it is almost impossible to go back over elicitations and do an analysis of how accurate they were in capturing the final costs.

There are some special characteristics of cost risk analysis that might justify modifications to elicitation practices in other fields. For example, cost risk analysts typically have to elicit many distributions in the course of doing a risk analysis for a complex project. The cost risk literature recommends doing a cost risk simulation using numbers of project elements (typically enumerated in the Work Breakdown Structure, or WBS) that are in the high tens to low hundreds.[22] In comparison, the outside elicitation literature typically works with many fewer elicitations. Documenting and archiving elicitation materials costs money, and there are currently no sources for such funds, at least in government organizations, without the interest and direction of senior leadership.

There are some indications that cost risk organizations in private industry do a more careful job of elicitation. However, these practices are considered proprietary and these organizations are reluctant to describe what they do in detail for public disclosure.

Current Best Practices in Elicitation

What practical advice can be given? While there seems to be much to consider and change in elicitation for cost risk analysis, a start can be made with the following procedure that is synthesized from a number of sources, including current practice in cost risk (Morgan and Henrion, 1990, Chaloner, 1996, and Meyer and Booker, 2001):

- Use multiple experts, if possible. If program engineers are used, independent engineers should also be included if feasible.

- Ask an expert to provide, at a minimum, upper, lower, and most likely values for cost of the WBS element under consideration (or for the technical characteristic that drives cost). During the elicitation the expert should be pushed to think of reasons why the range could be larger, especially in the upper direction and to explain the reasoning behind the answers. This will counteract tendencies to overoptimistically narrow distributions and will give the elicitor insight into issues that might be useful in further elicitation or analysis. While many cost risk analysts report that they ask for the most likely value first, the literature suggests that the central value should be elicited near the end to help counteract any effect of anchoring (Morgan and Henrion, 1990, p. 149, Spetzler and Von Holstein, 1975).

[22] Cost risk tools such as ACEIT from Tecolote Research can handle thousands of individual cost elements, probably too many to elicit.

- Fit a triangle distribution to the three numbers, but using the upper and lower values to bound 90% of the probability (where reasonable).[23] This adds some more spread to the distribution and helps to counteract over-optimism. See Figure 11-1 for a notional example where elicitation gave 300, 400, and 800 for the lower, most likely, and upper values. Using Garvey's procedure, for distributing the remaining 10%, we get a triangle distribution with 254 for the lower value and 985 for the upper value.

- Most current authors recommend eliciting at least two more percentiles. The two new percentiles may be formally inconsistent with fitting any triangle distribution to the three points recommended above, but could provide a valuable check. Also, it is recommended that percentiles be elicited in multiple ways to help check and diagnose bias.

- Provide feedback to the expert about the results of the elicitation, preferably in the same elicitation session. It would be very helpful to also be able to display historical data, if available.

- Carefully document the process and the results and archive the data obtained for future retrospective studies.

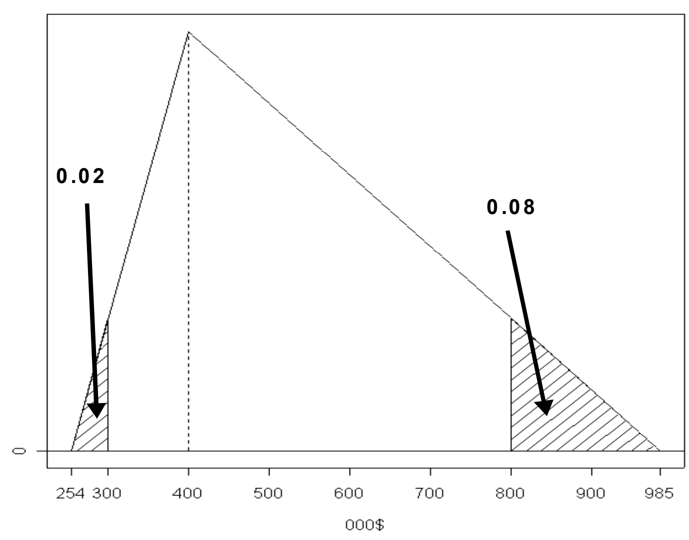

Figure 11-1-Fitting a Triangle Distribution to Upper, Lower, and Most Likely Values

Conclusions

The cost estimation community is in general agreement that probabilistic methods of quantifying and reasoning with uncertainty are the most rigorous methods of cost risk analysis. These methods may not always be used due to time and resources available or because of the detail required for the purposes at hand (Arena et.al., forthcoming). When relevant historical data are not available, elicitation of expert opinion is acknowledged to be a reasonable alternative. However, while there is emerging a set of criteria and procedures for careful, documented, controlled elicitation that attempts to deal with known biases (Morgan and Henrion, 1990, Meyer and Booker, 2001, Garthwaite et. al., 2004), it is fair to say that these procedures

[23] The triangle distribution is often used because of its simplicity, e.g. Morgan and Henrion, 1990, Book, 2001. The extension of the endpoints seems to be part of the folklore of practice: Garvey, 2000, gives some convenient formulas (used here) that distributes the remaining probability between the two tails in proportion to the skewness of the elicited upper and lower values. Biery, Hudak, and Gupta, 1994, recommend a variant, which divides the remaining probability equally between the two tails.

are not followed generally in the cost risk community, based on the interviews and on the available public literature. Further, to date there has been little comment on or explanation of this gap in the community.

This is not to say that elicitation research outside of the cost risk community has a definitive set of answers. The actual performance of elicitation procedures designed to minimize the classic biases of anchoring, optimism, etc. has not been extensively studied (see Mullin, 1986, for a partial example), and there may well be enhancements that are necessary to achieve the de-biasing required for more accurate assessments of uncertainty. There is also some evidence of substantial differences in the uncertainty judgments of expert vs. naive subjects, which means that some of the biases that have concerned researchers in the past may not be relevant to elicitation in cost risk.

However, elicitation practice in cost risk analysis needs to be significantly improved before it should begin to be concerned about issues such as these. Here are a number of steps that we believe the cost risk community should take to improve its use of elicitation.

- Assemble a reasonably complete list of current elicitation methods in use. This would include for example the "expanded triangle", but other methods may be in use that have not been described in the literature.

- The methods should be critically examined as to their theoretical and empirical underpinnings, using the wider elicitation literature.

- The performance of these methods in eliciting cost and the other uncertainties used in cost risk analysis should be tracked with empirical case studies and a database of elicited distributions and actual costs that occurred, with enough documentation to allow retrospective studies. Standards should be set for documenting the application of each of the methods to make it easier to assemble evidence for their strengths and drawbacks in particular situations.

These steps should provide cost risk analysts with a set of credible tools to do elicitation that can be compared and refined with further experience. The professional groups and major meetings in cost estimation (e.g. SSCAG, ISPA, DODCAS) and the cost estimation journals should encourage publication of such research, both theoretical and actual case studies and should insist that the reporting of the use of elicitation should be accompanied by information about the process used.

Finally, long-term studies of the performance of different methods in capturing uncertainties should be carried out by comparing elicited distributions with later actual costs. A long line of articles in the literature have consistently noted this key lack,[24] and virtually all cost analysts interviewed by the author agreed. Arguments against this endeavor include expense, lack of time by understaffed organizations, the long time-scales involved, and the unavoidable changes in projects. All of these factors make comparisons difficult, but without such comparisons, how can the value of elicitation be judged? The field is left with anecdotes or, worse, the suspicion that elicitation is only a crutch to get a set of numbers at the end that have no real value in helping to make decisions. Hilson, commenting on project risk management made this point explicitly (Hilson, 1998):

> In the absence of a coherent body of irrefutable evidence, the undoubted benefits that can accrue from effective management of risk must currently be taken on trust. Overcoming this will require generation of a body of evidence to support the use of formal project risk management, providing evidence that benefits can be expected and achieved, and convincing the skeptical or inexperienced that they should use project risk management.

[24] Beach, 1975, discussions of papers on "Elicitation", 1998, Meyer and Booker, 1991, Morgan and Henrion, 1990, O'Hagan, 1998, Hilson, 1998, Kitchenham, et.al., 2002.

Some of this information may be considered to be proprietary by commercial firms, notwithstanding their participation in and support of professional societies. However, government agencies such as the DoD and NASA have no such constraints and have an interest in assuring that the best procedures are available for all to use.

Finally, the cost risk field (and cost estimation in general) would be well served by using and citing relevant literature in other fields such as statistics and psychology. The quote by Wallenius cited above from the mid-1980s still holds true. In addition, the cost risk literature could be made more accessible outside of the field: the literature largely appears in specialized and sometimes short-lived journals, or in the proceedings of conferences which are difficult to access just a few years after publication. Collecting the literature and making it more easily available might be a worthwhile project for the professional societies supported by government and industry.

Cost risk analysis is in a unique position to contribute to the development of elicitation procedures: it has a need for elicitation to quantify significant uncertainties, it has many different opportunities in government and industry to apply these techniques and test them, and it has quantitatively sophisticated practitioners who can help advance the field of elicitation. But to do so, it has to take elicitation seriously and upgrade the techniques used across the profession.

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"An Assessment of Cost Risk Methodologies and Policies for the Air Force Cost Analysis Agency," (Arena et.al., forthcoming) in RAND's Project AIR FORCE division.

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12. Calculating Correlation from Cost Model Data

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Deriving Correlation Empirically

Deriving correlation coefficients that are specific to a cost model, such as the Unmanned Spacecraft Cost Model Version 7 (USCM-7), requires the analyst have access to the CERs and all of the data used to derive those CERs (Ref: [1]). In the case of USCM-7, correlation coefficients were derived using the CERs, lists of actual subsystem nonrecurring costs, recurring costs, and cost drivers programs in the USCM-7 cost database. The first step in the analysis is to use the CERs to calculate estimates for subsystem nonrecurring and first unit costs for all of the CERS and for all of the programs in the database. The next step is to calculate the residuals between actual costs and estimated costs for all of the CERs and for all of the programs in the database. Once this was completed, pair-wise subsystem residuals were used in the equation below to calculate the sample Pearson product -moment correlation, ρ_{XY}.

$$\rho_{XY} = \frac{\sum (x_i - x_m)(y_i - y_m)}{\sqrt{\sum (x_i - x_m)^2 \sum (y_i - y_m)^2}}, \qquad (37)$$

where x and y are CER residual pairs, x_i and y_i are individual program residual data, and x_m and y_m are and the mean of the residuals respectively.

If the two variables exactly follow a linear relationship (with no scatter), then the correlation coefficient $\rho = \pm 1$. Similarly, if there is no correlation between x and y, then the numerator, and thus r, should be zero.

Since the number of elements in the sample population (N=26, in the case of USCM-7) is considered a small sample, the sample correlation values were derived. Once the sample correlation coefficients were derived, their confidence intervals were derived. This probability is difficult to compute, but it can be done. Table 12-1 lists confidence intervals for various correlations and sample sizes. The rows represent N, the number of data points, and the columns are labeled with values for ρ.

For example, we used 26 data points, so a set of 20 to 30 data points would be uncorrelated at the 0.5% to 2.5% (1σ) confidence level if their correlation coefficient came out to 0.5. The results in Table 12-1 confirm that the correlation coefficients derived in this analysis are reasonable.

$$Z = \frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right) = 1.1513 * \log\left(\frac{1+\rho}{1-\rho}\right) \qquad (38)$$

the Z statistic is approximately normally distributed with mean and standard deviation:

$$\mu_Z = \frac{1}{2}\ln\left(\frac{1+\rho_0}{1-\rho_0}\right) = 1.1513 * \log\left(\frac{1+\rho_0}{1-\rho_0}\right) \quad (39)$$

$$\sigma_{Z=} = \frac{1}{\sqrt{N-3}} \quad (40)$$

Table 12-1 - Confidence Levels of Sample Correlation Coefficients

	ρ										
N	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
3	100	94	87	81	74	67	59	51	41	29	0
4	100	90	80	70	60	50	40	30	20	10	0
6	100	85	70	56	43	31	21	12	5.6	1.4	0
8	100	81	63	47	33	21	12	5.3	1.7	0.2	0
10	100	78	58	40	25	14	6.7	2.4	0.5	<0.1	0
15	100	72	47	28	14	5.8	1.8	0.4	<0.1	<0.1	0
20	100	67	40	20	8.1	2.5	0.5	0.1	<0.1	<0.1	0
30	100	60	29	11	2.9	0.5	<0.1	<0.1	<0.1	<0.1	0

Figure 12-1 illustrates the 95 percent confidence limits for the sample correlation values, ρ, for USCM 7. Note that the confidence limits are large when ρ is near zero and small when ρ is near $\pm$ 1.

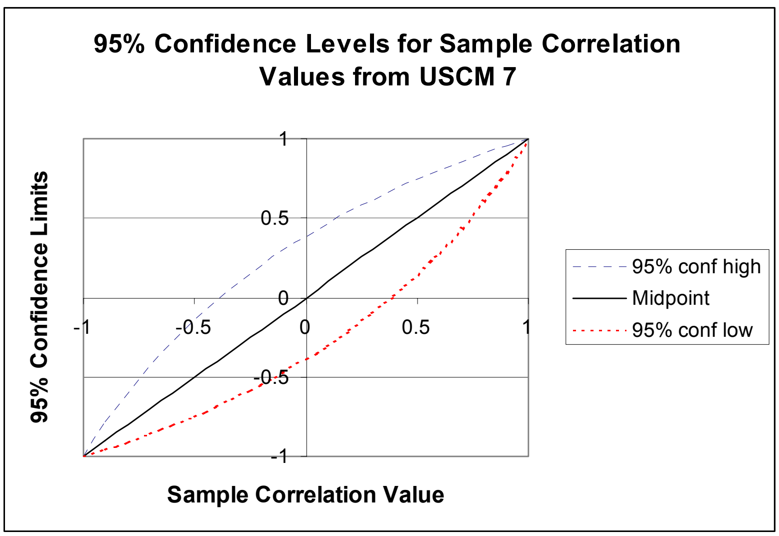

Figure 12-1 - 95th Percentile Confidence Levels for Sample Correlation Values from USCM-7

To illustrate the calculation of statistical correlation between residuals of a CER, we will use an example using the fictional database shown in Figure 12-2. It contains CER residual data for two CERs from eight programs. X_i and Y_i in the second and third columns represent the residuals of the two CERs for which we wish to determine the correlation. At the bottom of these columns is the mean of the residuals for the CERs. The fourth and fifth columns are calculations that represent the differences between the means of the residuals for both CERs for all eight programs. For each program, we multiply the values in column four and five to generate their product in column six. These values are then summed at the bottom of the column. Next, the values in columns four and five are squared to generate columns seven and eight. The sum of these squares is then reported at the bottom of the column. Finally, the sums at the bottom of columns six, seven and eight are used to determine the linear correlation coefficient.

PROGRAM	Error, Xi	Error, Yi	(Xi-Xm)	(Yi-Ym)	(Xi-Xm)(Yi-Ym)	(Xi-Xm)^2	(Yi-Ym)^2
1	0.5404	0.4224	0.1102	0.0167	0.0018	0.0121	0.0003
2	0.4943	0.3719	0.0641	-0.0339	-0.0022	0.0041	0.0011
3	0.4496	0.4340	0.0194	0.0282	0.0005	0.0004	0.0008
4	0.0088	0.2598	-0.4214	-0.1460	0.0615	0.1776	0.0213
5	0.5679	0.4291	0.1377	0.0234	0.0032	0.0190	0.0005
6	0.4486	0.5126	0.0184	0.1069	0.0020	0.0003	0.0114
7	0.7960	0.5357	0.3659	0.1300	0.0475	0.1339	0.0169
8	0.1359	0.2804	-0.2943	-0.1253	0.0369	0.0866	0.0157
SUM					0.1513	0.4340	0.0681
MEAN	0.4302	0.4057					
RHO	0.8804	= 0.151 / SQRT(0.434 * 0.068)					

$$\rho_{jk} = \frac{\sum (x_i - x_m)(y_i - y_m)}{\sqrt{\sum (x_i - x_m)^2 \sum (y_i - y_m)^2}}$$

Figure 12-2 - Sample Correlation Calculation Using Randomly Generated Numbers

The "CORREL" command in an Excel spreadsheet can perform this entire process.

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13. Formal Risk Assessment of System Cost Estimates (FRISK)

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Introduction

FRISK supports cost-risk analysis by allowing the user to statistically sum Work Breakdown Structure (WBS)-element costs, represented by probability distributions, to obtain a probability distribution of total cost. Its development was sponsored by the USAF Space and Missiles Systems Center (SMC/FMC) and, in the early 1990s, it was used in Acquisition Program Management Offices throughout the center. The theory behind FRISK was developed by Mr. Philip H. Young and originally programmed in Microsoft Quickbasic by Dr. Stephen A. Book, when both were with The Aerospace Corporation, El Segundo, CA. The FRISK mathematical process was later programmed in Excel by Raymond P. Covert of The Aerospace Corporation, Chantilly, VA, and (in a different version) by Erik L. Burgess.

To initiate the FRISK computational scheme, the user inputs low (most optimistic), most likely, and high (worst-case) costs for each WBS element, along with pairwise correlations between those elements. Expect for those persons using Mr. Burgess' Excel implementation, it is the user's responsibility to verify that the correlations assigned are consistent; i.e., that the correlation matrix is nonnegative definite, namely has no negative matrix eigenvalues. Based on the inputs, FRISK mathematics calculates the mean and variance of total cost.

Summation of WBS-element costs is done, not by Monte Carlo sampling, but by fitting a lognormal probability distribution to the mean and variance of total cost. (In the statistical literature, this technique is referred to as the "method of moments.") Percentiles of the lognormal distribution of total cost can be displayed (10th, 20th, ... , 90th, and 95th). A further capability allows the user the option of allocating a user-defined magnitude of "risk dollars" at the 50^{th} and 80^{th}, for example, percentile levels back to individual WBS elements. This latter capability was unique to FRISK software implementations throughout the 1990s and may still be.

Mathematical Principles Supporting FRISK

Unique mathematical characteristics of the triangular and lognormal probability distributions make them both especially applicable to cost analysis at these two stages of development and relatively easy to work with. The triangular distribution is the simplest probability distribution that a cost analyst can use to model his or her most basic knowledge of a WBS element's cost: its lowest possible cost (based on the most optimistic assumptions), its most likely cost (the "best" estimate), and its highest possible cost (based on worst-case risk-impacted assumptions). The lognormal distribution appears to be a good model for the statistical sum of either a small or a large number of triangular distributions.

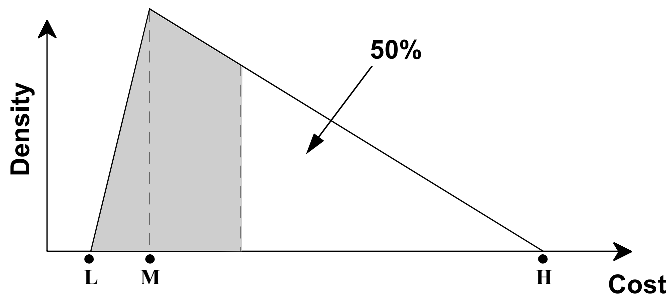

Figure 13-1 – Triangular PDF

All statistical properties of the triangular distribution, whose probability density function is pictured below, are uniquely determined by three parameters: the lowest possible cost L, the most likely cost *M*, and highest possible cost *H*. Algebraic details of the density function can be derived from the requirement that the area enclosed by the triangle be exactly 1.00. Additional statistical descriptors of the triangular distribution are its median,

$$T_{0.50} = L + \sqrt{0.50(M-L)(H-L)} \quad \text{if } M\text{-}L \geq 0.50(H\text{-}L) \tag{41}$$

$$= H - \sqrt{0.50(H-L)(H-M)} \quad \text{if } M\text{-}L \leq 0.50(H\text{-}L),$$

its mean,

$$\mu = \frac{L+M+H}{3}, \tag{42}$$

and its standard deviation,

$$\sigma = \sqrt{(L^2 + M^2 + H^2 - LM - LH - MH)/18}. \tag{43}$$

The lognormal distribution, whose probability density function is pictured below, is

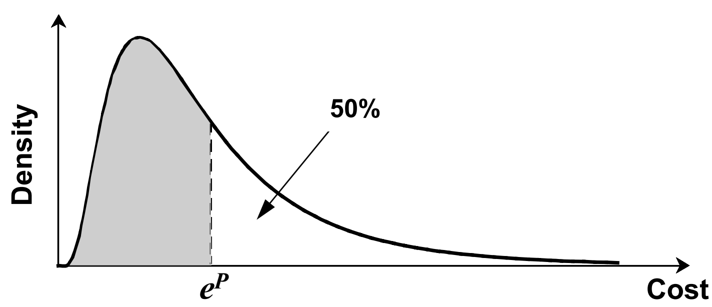

Figure 13-2 - Lognormal PDF

the exponentiation of an underlying normal (Gaussian) distribution. Its statistical behavior is uniquely determined by one of two sets of two parameters each: either (1) its own mean μ and its own standard deviation σ or (2) the mean P and standard deviation Q of the underlying normal distribution. There are simple algebraic transformations between the two sets of parameters, making it easy to express statistical descriptors in terms of either set:

$$\begin{aligned}
\mu &= \exp(P + \frac{1}{2}Q^2) \\
\sigma &= [\exp(P + \frac{1}{2}Q^2)]\sqrt{\exp(Q^2) - 1} \\
P &= \frac{1}{2}\ell n\left(\frac{\mu^4}{\mu^2 + \sigma^2}\right) \\
Q &= \sqrt{\ell n\left(1 + \frac{\sigma^2}{\mu^2}\right)}.
\end{aligned} \tag{44}$$

Once the mean P and the standard deviation Q of the underlying normal distribution are calculated, the relationship between the lognormal and normal distributions is invoked. The table of the standard normal distribution (commonly available in elementary statistics textbooks) is used to calculate the percentiles of total cost, which is represented by the fitted lognormal distribution.

Allocating Risk Dollars back to WBS Elements

Asymmetry in the probable magnitude of the difference between actual project cost and the so-called "best estimate" often leads users of common estimating methods, such as "rolling up" (i.e., adding) most-likely costs of the various project elements, to underestimate actual project cost. Because of the uncertainties in actual cost, it is useful to model project cost as a random variable and to express cost estimates in terms of percentiles of its probability distribution. After a project is finally budgeted at whatever level is considered its “best-estimate” cost, it is prudent to prepare a "management reserve" of additional funds to overcome unanticipated contingencies that may deplete the budget prior to project completion. Percentiles of the cost probability distribution can serve as guidelines for the size of an appropriate management reserve. Suppose, for example, that the number submitted as the best estimate falls at the 40th percentile level of the cost probability distribution. Depending on the criticality of the project, a prudent management reserve might consist of the funding required to bring the total amount of available dollars to the 50th, 70th, or even 90th percentile.

Because of the many factors (most of which have highly uncertain impacts) that influence the cost of each element of a development program’s work-breakdown structure (WBS), we have noted that it is useful to treat WBS-element costs as if they were random variables rather than fixed numbers. To act on the notion of cost as a random variable, we model each WBS element’s cost as a probability distribution. Once a probability distribution is established for the cost of each WBS element and a correlation matrix defined, the probability distribution of total cost is derived by combining the WBS-element cost probability distributions statistically, either by Monte Carlo sampling or other appropriate procedure. To fix the context of our discussion, let’s agree that the most-likely total cost is to be sent forward as the “best estimate” and cost-risk is to be accounted for by asking for the 70th-percentile dollar amount to serve as a reasonable “management reserve.” By the term “risk dollars,” we mean the amount of funding beyond the best-estimate up to the 70th percentile. That is, the number of risk dollars is calculated as follows:

Risk dollars = 70th-percentile cost – Best-estimate cost. (45)

Dollars in the management reserve pool, referred to as "risk dollars," may in some cases constitute a noticeably large percentage of the budgeted best-estimate funding base. Funding agencies are typically reluctant to set aside such large amounts of money for management reserve, believing that such pots of "slush funds" lead to sloth, waste, inefficiency, and generally slack management. Furthermore, some of those providing the funding consider management reserves to rank slightly below "slush funds" on the decency scale, so it is necessary to provide logical justification for such requests by displaying in a defensible way an allocation of the requested risk dollars among the various project elements. The present section suggests a mathematical procedure that will allow the analyst to allocate risk dollars among project elements in a manner that is logically justifiable and consistent with the original goals of the cost-estimating task.. A specific WBS-based cost-risk analysis can profile a probable need for additional moneys beyond those included in the best estimate.

Because a WBS element's "need" for risk dollars arises out of the uncertainty in the cost of that WBS element, a quantitative description of that "need" should be the logical basis of the risk-dollar computation. In general, the more uncertain the cost is, the more risk dollars will be needed to cover a reasonable probability (e.g., 0.70) of being able to complete that element of the system. As a way of introducing the subject of "need", let's first note that the first-order measure of uncertainty in statistics is the variance or "sigma-squared." Generally, a probability distribution with a larger sigma-squared value tends to range over a larger region of the cost axis, and therefore the corresponding WBS element is characterized by more uncertainty in its cost.

However, more precision is involved than simply sigma-squared. Suppose the WBS has only three elements, *i*, *j*, and *k*, and suppose σ_i^2, σ_j^2 and σ_k^2 are the sigma-squared values of those elements. If the costs of the elements are pairwise uncorrelated, then the sigma-squared value of the total cost is given by $\sigma_i^2 + \sigma_j^2 + \sigma_k^2$. We can then allocate risk dollars to the three WBS elements in the same proportions as their uncertainties, i.e., the fraction $\sigma_i^2 / (\sigma_i^2 + \sigma_j^2 + \sigma_k^2)$ to element i, the fraction $\sigma_j^2 / (\sigma_i^2 + \sigma_j^2 + \sigma_k^2)$ to element *j*, and the fraction $\sigma_k^2 / (\sigma_i^2 + \sigma_j^2 + \sigma_k^2)$ to element *k*. Suppose, however, that costs of the first two WBS elements are positively correlated with correlation coefficient ρ_{ij}, and that their correlation with element *k* is zero. Then elements *i* and *j* would "need" a greater fraction of risk dollars than is indicated by the above proportion because of their impact on each other, i.e., because uncertainty or risk in WBS element *i* induces additional risk in WBS element *j*, beyond that which would be anticipated by the previously-cited fraction alone. This example shows that inter-WBS-element correlations must be taken into account in properly allocating risk dollars back to the individual WBS elements.

If the correlation structure is as indicated in the latter portion of the above paragraph, then the total-cost sigma-squared is not $\sigma_i^2 + \sigma_j^2 + \sigma_k^2$, but is actually

$$\sigma_i^2 + \sigma_j^2 + 2\rho_{ij}\sigma_i\sigma_j + \sigma_k^2, \tag{46}$$

which can be written more suggestively as

$$(\sigma_i^2 + \rho_{ij}\sigma_i\sigma_j) + (\sigma_j^2 + \rho_{ij}\sigma_i\sigma_j) + \sigma_k^2. \tag{47}$$

[Note: If all three WBS-element costs were inter-correlated, the total-cost sigma-squared would be

$$\sigma_i^2 + \sigma_j^2 + \sigma_k^2 + 2\rho_{ij}\,\sigma_i\sigma_j + 2\rho_{ik}\sigma_i\sigma_k + 2\rho_{jk}\sigma_j\sigma_k, \tag{48}$$

where the double subscript on ρ indicates the two elements that are correlated.]

The additional uncertainty in the total cost, in the amount of $2\rho_{ij}\sigma_i\sigma_j$, that results from inter-WBS-element correlation is divided, for allocation purposes, between the two correlated WBS elements *i* and *j*. Therefore the fraction of risk dollars that should be allocated to element *i* becomes

$$(\sigma_i^{\,2} + \rho\sigma_i\sigma_j)/[(\sigma_i^{\,2} + \rho\sigma_i\sigma_j) + (\sigma_j^{\,2} + \rho\sigma_i\sigma_j) + \sigma_k^{\,2}], \tag{49}$$

Then the fraction of risk dollars that should be allocated to element *j* becomes

$$(\sigma_j^{\,2} + \rho\sigma_i\sigma_j)/[(\sigma_i^{\,2} + \rho\sigma_i\sigma_j) + (\sigma_j^{\,2} + \rho\sigma_i\sigma_j) + \sigma_k^{\,2}], \tag{50}$$

and the fraction of risk dollars that should be allocated to element *k* becomes

$$(\sigma_k^{\,2})/[(\sigma_i^{\,2} + \rho\sigma_i\sigma_j) + (\sigma_j^{\,2} + \rho\sigma_i\sigma_j) + \sigma_k^{\,2}], \tag{51}$$

because element *k* has no correlated need.

While the above discussion appears to make sense, it turns out that this method of allocating risk dollars back to the WBS elements is not exactly valid. The reason is that sigma-squared does not distinguish between above-the-average uncertainty and below-the-average uncertainty. For example, the triangular distributions in the two diagrams below both have the same sigma-squared, although only the WBS element whose distribution is on the right “needs” an allocation of risk dollars:

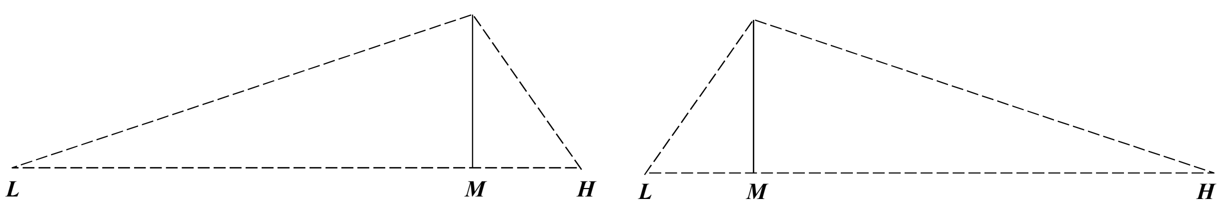

Figure 13-3 - Triangular distributions

Yet the procedure we have outlined here would allocate the same amount of risk dollars to both elements above. Obviously, we have not correctly measured the need for risk dollars.

In order to “correctly” measure the uncertainty in each WBS element’s cost, we must account for the extent to which the element’s most-likely estimated cost fails to reflect an appropriate probability of being sufficient to fund the element’s completion as required. If the total system is to have a management reserve to cover the probability at the 70% level, then we can define the “need” of WBS element *k* to be the difference between its own 70th-percentile cost and its most-likely estimated cost, i.e.,

$$Need_k = (70th\ Percentile\ Cost)_k - (Most\ Likely\ Cost)_k, \tag{52}$$

but $\qquad Need_k = 0 \qquad$ if $\quad (70th\ Percentile\ Cost)_k \le (Most\ Likely\ Cost)_k$

plus any correlation effects due the impacts of the needs of other WBS elements with which element *k* is correlated. Here $Need_k$ can be considered as the above-average portion of σ_k, measuring only the possible shortfall in funding due to realization of any anticipated risk issues.

Given a system, then, that consists of *n* WBS elements, we replace each sigma-value in the previous section by the corresponding "correct" measure of WBS-element need and obtain an expression for the "Total Need Base", including correlation effects, as follows:

$$\textit{Total Need Base} = \sum_{k=1}^{n} Need_k^{\,2} + 2\sum_{k=2}^{n}\sum_{j=1}^{k-1}\rho_{jk}\, Need_j\, Need_k \tag{53}$$

$$= \sum_{k=1}^{n}\left(Need_k^{\,2} + \sum_{j=1(j\neq k)}^{n}\rho_{jk}\, Need_j\ Need_k\right) = \sum_{k=1}^{n}\ \sum_{j=1}^{n}\rho_{jk}\, Need_j\, Need_k\,.$$

Recall that, if $j = k$, then $\rho_{jk} = 1$, so that, for each WBS-element *k*, the need including correlation effects is given by $\sum_{j=1}^{n}\rho_{jk}\, Need_j\, Need_k$. This means that the fraction of risk dollars to be allocated to element *k* is given by the following expression:

Fraction of Risk Dollars allocated to Element k

$$= \frac{Need\ \ of\ \ Element(k)}{Total\ \ Need\ \ Base} = \left(\sum_{j=1}^{n}\rho_{jk}\, Need_j\, Need_k\right) / \left(\sum_{k=1}^{n}\ \sum_{j=1}^{n}\rho_{jk}\, Need_j\, Need_k\right) \tag{54}$$

Multiplying this fraction times the total number of risk dollars available yields the number of risk dollars to be allocated to cover risk issues associated with WBS element *k*.

Cost Risk Examples Using Popular Cost Models

14. Automated Cost Estimator (ACE)

Alf Smith
Tecolote Research, Inc.

Overview and Risk Capability

ACE, the Automated Cost Estimator, is a Government funded, special purpose program, specifically developed for cost analysis. It automates the primary tools and techniques of the cost analysis trade, such as WBS structures, inflation, learning, time phasing, cost as an independent variable (CAIV), cost-category reports, documentation, sensitivity/what-if analysis and risk analysis.

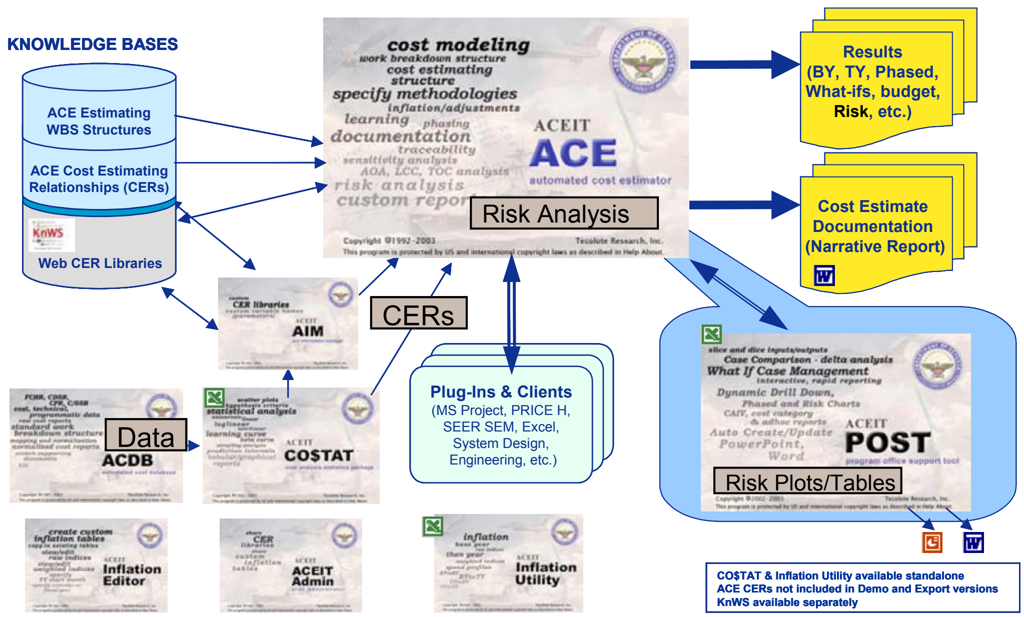

Figure 14-1 - Automated Cost Estimator Block Diagram

RI$K is an ACE provided capability that allows you to conduct a risk analysis on the cost, schedule, and technology uncertainty in your cost estimate. ACE uses a modified Monte Carlo technique based on the Latin Hypercube method for simulating the specified distributions and their associated interactions (both through the CERs and their inputs) to derive aggregate or parent level distributions. RI$K incorporates a Pearson-Product Moment correlation technique similar to that of the Laurie-Goldberg algorithm for creating a set of variables that match a supplied correlation matrix [1].

RI$K Example

We will use the FireSat Cost estimate (introduced and discussed in detail in Section 3) in Wertz and Larson [2] as the basis for a demonstration of how to conduct a risk analysis in ACE. We will take some liberties and use derived data to illustrate how users can begin the risk analysis process by generating the CER in CO$TAT. By doing so, the analyst can objectively quantify risk in their cost model and pass that information to the cost model in ACE. For this demonstration, linear ordinary least squares is used to generate the "220 * KSLOC" equation from dummy information. The dummy information was designed to reproduce the risk range as provided Section 3 of this manual. Ten data points (only the first six are visible in the illustration) are used. A summary of the statistical results is provided in Figure 14-2.

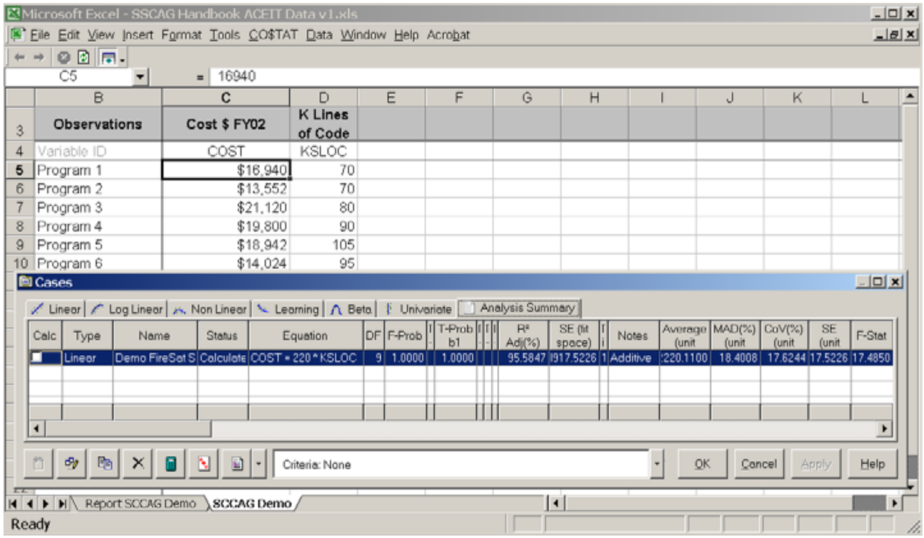

Figure 14-2 - FireSat software "dummy" data

The most accurate approach to establish the bounds of your CER risk is to calculate the prediction interval for your specific estimate. Figure 14-3 shows the statistical results of this process. In this case, the point estimate KSLOC is 100. By asking CO$TAT to compute the 80% confidence level, CO$TAT will calculate the bounds of the normal distribution that describes the prediction interval of the CER for 100 KSLOC by calculating the bounds at the 10% and 90% percentile (80% confidence interval). These are the default bounds. The user may calculate the bounds at any desired confidence level and ACE will use them to define the risk distribution.

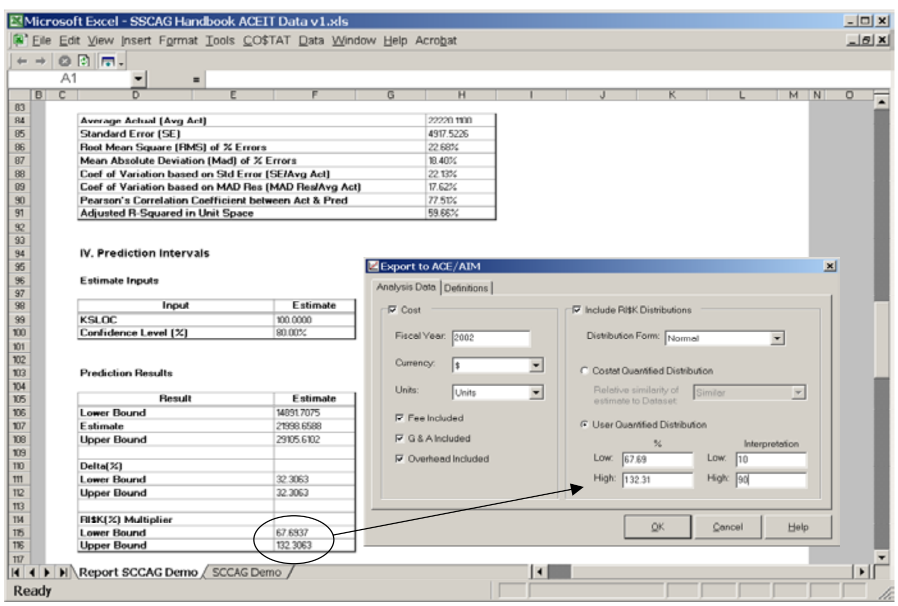

Figure 14-3 - Statistical results of FireSat software CER

Readers should not assume that they are "locked in" to using CO$TAT to define their CER risk distributions. The CER and risk distribution can be entered explicitly. In the case of the FireStat model, we are given the functional relationships, a point estimate, a standard deviation and some correlation assumptions. ACE promotes mechanisms to define the variation in the cost estimate such that they will scale with the point estimate. A convenient way to accomplish this for the FireSat case is to divide the given standard deviation by the point estimate to give (in the case of a normal distribution) the coefficient of variation. In ACE, this value may be entered directly into the "Spread" column on the risk worksheet for version 6.0a and earlier. For ACEIT 7.0 and above (due late summer 2006) there will be a column dedicated to this kind of entry. By doing this, as the point estimate changes, the standard deviation will scale accordingly. This avoids a huge "pitfall" in many risk estimates where the analyst makes, perhaps hundreds, of last minute changes to the estimate and either forgets of does not have the time to update standard deviations accordingly.

The CER, its meaning ($, units, adjustments included), the entire statistical report (not shown) and the risk specifications are passed automatically to ACE. If the source data changes, it is a simple matter to update the CER, risk assessment and supporting documentation automatically. All of the data will be passed to the position (row) in the ACE session selected by the user. In the illustration below, some of the data that was passed to ACE is shown.

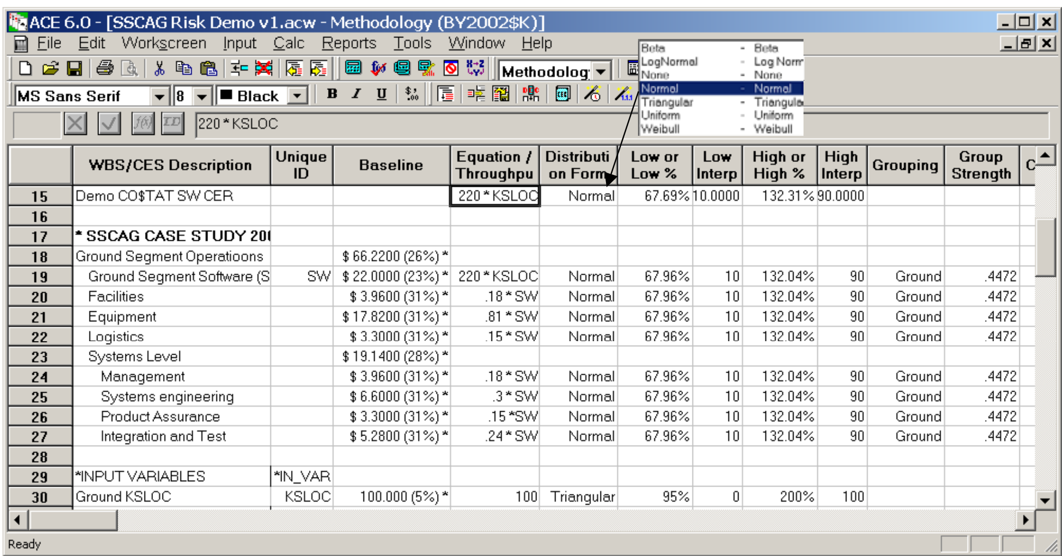

Figure 14-4 - COSTAT output passed to ACE

Statistics and correlation parameters from a previous example are used in the model. The ACE RI$K screen has the following fields:

Table 14-1 - ACE RI$K data fields

WBS/CES Description	Cost element description
Distribution Form	Normal, Log-Normal, Triangular, Beta, Uniform, Weibull
Log Normal Adjusted SE	Standard error (SE) (in log space), adjusted for the number of data points and distance from the data center can be used to characterize the levels of dispersion for log-normal distributions. Its value must be between 0.0 and 1.0.
Low or Low % High or High %	Defines the low/high value for the element. The value can be specified either as a percent (recommended) or as a specific value.
Low Interpretation High Interpretation	Specifies the confidence level at which to interpret the Low or Low % and High or High %.
Spread	This field is used to define the dispersion or variance about the mode for all distribution types in qualitative terms. The acceptable values are LOW, MEDIUM, and, HIGH.
Skew	Defines how a Uniform, Triangular, or Beta distribution is skewed if "Spread" is used to define its dispersion. How far a distribution is skewed right or left is a function of the spread.
Schedule/Technology	This field is used to incorporate schedule and technology uncertainty (e.g., penalty factors) in the RI$K estimate. The penalty factor essentially "stretches" the upper bound of the defined distribution.
Grouping	Used to identify elements that are correlated with one another.
Group Strength	This field is used to specify the strength of the group association. Cost elements can have positive and negative correlations. If a dominant element is selected, the Group Strength represents the pair wise Pearson product moment correlation coefficient. If there is no dominant element, the correlation achieved in the simulation is the square of the Group Strength value. For instance, to establish a correlation matrix with 20% in every cross correlation, the user would enter 0.45 for the Group Strength value of each element in the group.

Distribution bounds are defined as either absolute values or as a percent of the point estimate. The latter is recommended, as this will render the bounds applicable to any sensitivity analysis that is conducted. For instance, consider a point estimate of where the baseline point estimate for the KSLOC is 100 and the bounds are set to be 95 and 200. If the user subsequently investigates an alternative where the point estimate KSLOC is 250, then the bounds must be adjusted as well. If, however, the bounds are set to 95% and 200% of the point estimate, then the risk distribution will scale with the point estimate.

We highly recommend that before you set about specifying correlation, use the ACE Correlation Report Utility to explore the correlation established by the functional relationships in your cost model. Often, you will find correlations present in your model that you may not have expected. In the case study under consideration, measuring first is particularly insightful. Table 14-2 illustrates the correlations that exist in the model when the risk is applied to KSLOC and all the WBS elements in the cost model. As you can see, there is significant cross correlations already present by virtue of the factor relationship with the Ground Segment Software element.

Table 14-2 - Correlations that result from functional correlation

SSCAG Risk Demo v1.acw - RI$K Correlation (FY2002 K, RIK Correlation, Case: Baseline)

	WBS/CES	Row 47: Ground	Row 48: Ground	Row 49: Faciliti	Row 50: Equip	Row 51: Logisti	Row 52: Systems	Row 53: Manag	Row 54: Systems	Row 55: Product	Row 56: Integration	Point Estimate	Mean	Std Dev	CoV
46	* SSCAG CASE STUDY No Corr														
47	Ground Segment Operatioons	1.00	0.97	0.78	0.88	0.77	0.93	0.78	0.79	0.77	0.78	$ 66.2 (23%)	$ 87.2	$ 28.3	0.32
48	Ground Segment Software (SW)		1.00	0.77	0.77	0.77	0.92	0.77	0.76	0.77	0.77	$ 22.0 (22%)	$ 29.0	$ 9.1	0.31
49	Facilities			1.00	0.59	0.60	0.71	0.59	0.59	0.59	0.60	$ 4.0 (30%)	$ 5.2	$ 2.1	0.41
50	Equipment				1.00	0.59	0.70	0.59	0.58	0.59	0.59	$ 17.8 (30%)	$ 23.5	$ 9.6	0.41
51	Logistics					1.00	0.70	0.60	0.58	0.58	0.59	$ 3.3 (30%)	$ 4.3	$ 1.8	0.41
52	Systems Level						1.00	0.81	0.87	0.78	0.84	$ 19.1 (25%)	$ 25.2	$ 8.6	0.34
53	Management							1.00	0.59	0.59	0.59	$ 4.0 (30%)	$ 5.2	$ 2.2	0.41
54	Systems engineering								1.00	0.58	0.59	$ 6.6 (30%)	$ 8.7	$ 3.5	0.41
55	Product Assurance									1.00	0.59	$ 3.3 (30%)	$ 4.3	$ 1.8	0.41
56	Integration and Test										1.00	$ 5.3 (30%)	$ 7.0	$ 2.8	0.41

Table 14-3 illustrates how the correlation matrix is influenced after inducing an additional 20% correlation across all elements (i.e., apply a Group Strength of 0.4472 across all elements). The cross correlations increase by about 10%. The mean at the total level does not change, however the standard deviation increases by 10%. In this case, adding an additional 20% of correlation does not have a tremendous impact. The cost at the 90% level, for instance, only changes by about 3%. Many would argue that this is an insignificant difference. If, however, this estimate was populated with independent CERs, layering an additional moving the average correlation from "zero" to 20% would have a very big impact on cost. In this case, we were moving average functional correlations of near 60% to 70%. And, as you can see in the example, this has minimal impact on the total cost.

Table 14-3 - Correlations after inducing 20% correlation across all WBS elements

SSCAG Risk Demo v1.acw - RI$K Correlation (FY2002 K, RIK Correlation, Case: Baseline)

	WBS/CES	Row 18: Ground	Row 19: Ground	Row 20: Faciliti	Row 21: Equip	Row 22: Logisti	Row 23: Systems	Row 24: Manag	Row 25: System	Row 26: Product	Row 27: Integration	Point Estimate	Mean	Std Dev	CoV
17	* SSCAG CASE STUDY 2004														
18	Ground Segment Operatioons	1.00	0.96	0.84	0.92	0.84	0.96	0.84	0.86	0.84	0.85	$ 66.2 (25%)	$ 87.9	$ 31.1	0.35
19	Ground Segment Software		1.00	0.81	0.81	0.81	0.91	0.81	0.81	0.81	0.81	$ 22.0 (23%)	$ 29.0	$ 9.1	0.31
20	Facilities			1.00	0.72	0.71	0.80	0.71	0.71	0.72	0.71	$ 4.0 (31%)	$ 5.3	$ 2.3	0.44
21	Equipment				1.00	0.72	0.80	0.71	0.72	0.72	0.72	$ 17.8 (31%)	$ 23.8	$ 10.3	0.43
22	Logistics					1.00	0.81	0.71	0.72	0.72	0.72	$ 3.3 (31%)	$ 4.4	$ 1.9	0.44
23	Systems Level						1.00	0.87	0.91	0.86	0.89	$ 19.1 (28%)	$ 25.5	$ 9.9	0.39
24	Management							1.00	0.71	0.72	0.72	$ 4.0 (31%)	$ 5.3	$ 2.3	0.43
25	Systems engineering								1.00	0.72	0.71	$ 6.6 (31%)	$ 8.8	$ 3.8	0.43
26	Product Assurance									1.00	0.72	$ 3.3 (31%)	$ 4.4	$ 1.9	0.44
27	Integration and Test										1.00	$ 5.3 (31%)	$ 7.0	$ 3.0	0.43

In Figure 14-5, the impact of the correlation between the Ground Segment Software and the other elements in the estimate based upon the risk assumptions applied to the cost model are illustrated. As one would expect, all the other elements are fully correlated with the Ground Segment Software cost (because they are factors of it) when risk is only applied either to the KSLOC or both the KSLOC and the SW CER. When risk is applied to the factors, the correlation drops to around 78%. In the case study, we apply a 20% correlation to the factor risk distributions and the net effect is an increase of about 10%. The net effect of the layering of KSLOC risk, CER risk and perfectly correlated factor risk is about 95% correlation overall.

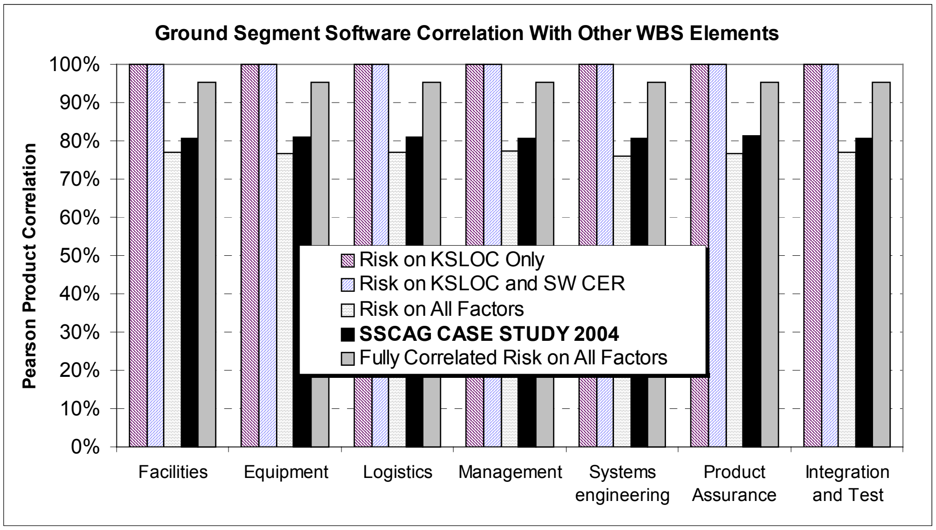

Figure 14-5 - Impact of correlation based on risk assumptions

The real question, however, is how does the layering of risk assumptions impact the cost results. Figure 14-6 illustrates that in this particular case study, the application of 20% risk across all elements has no significant impact at the 80% confidence level. In fact, once risk has been applied to the KSLOC and the SW CER, adding risk to the factors is not important unless you plan to apply very broad distributions or very significant correlation.

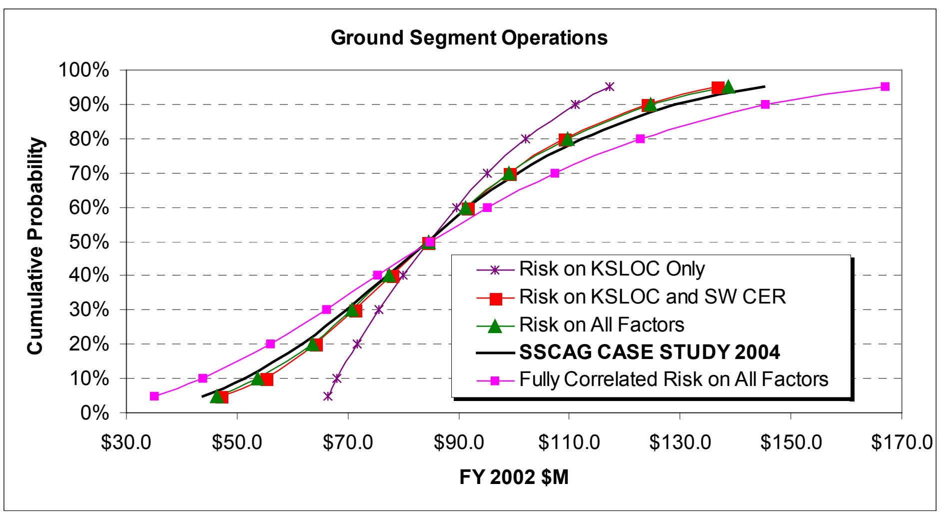

Figure 14-6 - Application of 20% risk across all elements has no significant impact at the 80% confidence level.

The following table compares ACE, Crystal Ball and @Risk results.

Table 14-4Comparison of ACE, Crystal Ball and @Risk results

	Point Estimate	CER/Thruput	Risk	Analytic Stdev	ACE Stdev	CB Stdev	@Risk Stdev
Ground Segment Operatioons	66,220				31,014	30,975	31,322
Ground Seg Software (**SW**)	22,000	220 * KSLOC	N(1, 0.25^2)	9,084	9,039	9,027	9,101
Facilities	3,960	.18 * SW	N(1, 0.25^2)		2,289	2,283	2,321
Equipment	17,820	.81 * SW	N(1, 0.25^2)		10,309	10,254	10,360
Logistics	3,300	.15 * SW	N(1, 0.25^2)		1,895	1,900	1,922
Systems Level	19,140				9,844	9,835	9,925
Management	3,960	.18 * SW	N(1, 0.25^2)		2,281	2,271	2,311
Systems engineering	6,600	.3 * SW	N(1, 0.25^2)		3,824	3,812	3,848
Product Assurance	3,300	.15 * SW	N(1, 0.25^2)		1,902	1,919	1,920
Integration and Test	5,280	.24 * SW	N(1, 0.25^2)		3,047	3,055	3,068
Ground Software **KSLOC**	100	100	T(0.95, 1, 2)	24.18	24.18	24.18	24.18

Ground Segment Operations						
$K	**Mean**	**5%**	**10%**	**50%**	**90%**	**95%**
ACE	$87.9	$43.5	$51.6	$84.2	$128.8	$144.4
CB	$87.9	$43.4	$51.4	$84.1	$130.2	$144.1
	0.0%	0.2%	0.4%	0.1%	-1.0%	0.2%

Figure 14-7 - Comparison of ACE and Crystal Ball results

Points of Contact

Web Site

http://www.aceit.com/ or **aceit_support@tecolote.com**

http://www.tecolote.com/Products/Products.htm

Point of Contact

Alf Smith Tecolote Research Inc. 805 964-6963

References

[1] Hu, Shu-Ping and Smith, A., “Impact of Correlating CER Risk Distributions on a ‘Realistic’ Cost Model,” Tecolote Research, Inc., SCEA, June 2003.

[2] Wertz, James R. and Larson, Wiley J., Space Mission Analysis and Design, 3rd Edition, Microcosm Press and Kluwer Academic Publishers, 1999.

15. NASA/Air Force Cost Model (NAFCOM)

Sharon Winn and Christian Smart, Ph.D.
SAIC

Overview

NAFCOM is a parametric cost estimating tool for space hardware that uses cost estimating relationships (CERs) that correlate historical costs to mission characteristics to predict new project costs The CERs are based on historical NASA and Air Force space projects and are intended to be used in the early phases of a development project. NAFCOM can be used at the subsystem or component levels to estimate development and production costs. It is applicable to manned spacecraft, unmanned spacecraft, and launch vehicles. NAFCOM also includes a large cost database as well as several other tools, including process-based scheduling, time-phasing of cost, functional breakout structures, PRICE-H calibration factors, cost trades capability, and funding profiles.

The NAFCOM Database contains cost, technical, and programmatic data at the component, subsystem, and system level for the 100 unmanned spacecraft, 8 manned, 11 launch vehicle stages, and 3 liquid rocket engines contained in the NAFCOM Cost Model. The Scientific Instrument Database provides instrument level cost for 366 scientific instruments from 100 unmanned and 8 manned spacecraft.

Risk analysis is a new feature in NAFCOM 2004. The risk calculations are performed using analytic approximation, which involves separately summing means and variances for each WBS cost element, taking correlation into account, and then fitting distributions to the top-level means and variances. We chose an analytic method because we wanted a method that is computationally as simple as possible while still providing accurate estimates; calculates the correct top-level means and standard deviations; is faster than Monte Carlo; and allows the user full access to the correlation matrix. The user can set individual inter- and intra-subsystem correlations to any desired value in the range (-1,1). Recent comparison tests have demonstrated close agreement between Monte Carlo simulations and the method implemented in NAFCOM.

Technical and Estimating Risk

NAFCOM's risk analysis capabilities incorporate both technical risk and estimating risk. Technical risk accounts for uncertainty in the CER inputs – weight, technical and management parameters, and other cost drivers. Technical risk is represented by a triangular distribution. The user determines the parameters of the triangular distribution by inputting low, most likely, and high values for each cost driver.

Estimating risk accounts for the uncertainty inherent in the CERs. The NAFCOM CERs assume multiplicative error. The triangular distribution mean and variance for technical risk are used to define a lognormal distribution, which is then multiplied by the lognormal estimating error distribution. This distribution is a lognormal distribution. This process is illustrated in Figure 15-1.

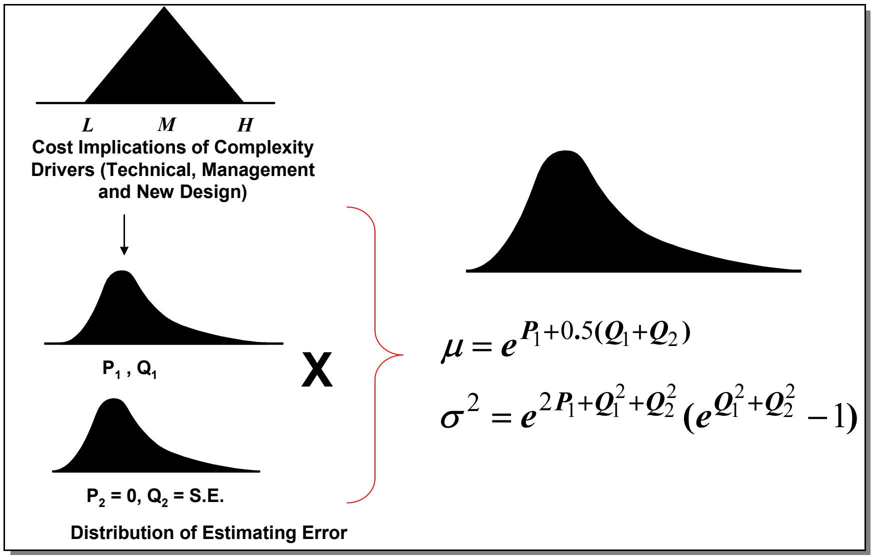

Figure 15-1 - Combining Technical and CER Risk

Note that in Figure 15-1, the parameters P_1, P_2, Q_1, and Q_2 represent the first two moments of the corresponding "log space" normal distributions for each lognormal distribution. P_1 and Q_1 represent the mean and standard deviation (respectively) for the technical risk lognormal distribution and P_2 and Q_2 represent the "log space" mean and standard deviation (respectively) for the CER risk lognormal distribution. The relationship between P and Q and the lognormal distribution μ and σ is contained in the following formulas.

$$P = \frac{1}{2}\ell n\left(\frac{\mu^4}{\mu^2+\sigma^2}\right)$$

$$Q = \sqrt{\ell n\left(1+\frac{\sigma^2}{\mu^2}\right)} \qquad (55)$$

The method of moments is used to sum the means and variances for each WBS hardware element, taking correlation into account.

The correlation matrix is an $n \times n$ upper-triangular matrix:

$$\begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1n} \\ & 1 & \rho_{23} & \cdots & \rho_{2n} \\ & & 1 & \cdots & \rho_{3n} \\ & & & \ddots & \vdots \\ & & & & 1 \end{bmatrix} \qquad (56)$$

We then calculate the mean and standard deviation of total cost by summing the individual WBS-element means and variances (squares of the standard deviations):

$$\text{Total-Cost Mean} = \sum_{k=1}^{n} \mu_k \qquad (57)$$

and

$$\text{Total-Cost Standard Deviation} = \sqrt{\sum_{k=1}^{n} \sigma_k^{\ 2} + 2\sum_{k=2}^{n}\sum_{j=1}^{k-1} \rho_{jk}\sigma_j\sigma_k} \ . \qquad (58)$$

The default correlation values are 0.2 for inter-subsystem elements, and 0.5 for intra-subsystem elements.

Systems Test Hardware and Systems Engineering

NAFCOM calculates systems test hardware (STH) cost as a percentage of flight unit cost. This cost is then multiplied by the number of test units. That is,

STH Cost = % Flight Unit Cost*Flight Unit Cost* Number of Test Units. (59)

This calculation is performed for each WBS or subsystem element. The default inputs are 130% for percent of flight unit cost and 1 for the number of test units. However, the user may select any positive value for percent of flight unit cost and any positive real number for the number of test units.

Lognormal distributions are preserved under scaling, that is, if X is a lognormally distributed random variable, then the random variable kX is also lognormally distributed, where k can be any real number. Also, a statistic for the random variable kX – any percentile, the mean, or the standard deviation – is the product of k and the corresponding statistic for X, so for example if μ is the mean of X, then $k\mu$ is the mean of kX. Denotehe flight unit's cost distribution mean and standard deviation by μ and σ. Then the mean and standard deviation for STH are:

mean = μ∗% Flight Unit Cost * Number of Test Units (60)

standard deviation = σ∗% Flight Unit Cost * Number of Test Units (61)

By definition, DDT&E cost = Design and Development (DD) Cost + STH Cost. The mean and standard deviation for DDT&E cost are:

$$\mu_{DDT\&E} = \mu_{DD} + ab\mu_{FU} \qquad (62)$$

$$\sigma^2_{DDT\&E} = \sigma^2_{DD} + (ab)^2\sigma^2_{FU} + \rho_{DD,FU}\sigma_{DD}\sigma_{FU} \ , \qquad (63)$$

where a = % Flight Unit Cost, b = Number of Test Units.

The STH and DDT&E moments are rolled up to the total level using the FRISK methodology, just as for the DD and Flight Unit moments.

Systems engineering costs are calculated in NAFCOM as a function of total system hardware cost. The model has the power equation form:

$$Y = a(\mathit{Total\ Hardware\ Cost})^b \qquad (64)$$

The above equation is the general form used for the CERs for Systems Test Operations, Tooling, Mechanical/Electrical Ground Support Equipment, Systems Engineering and Integration, Project Management, and Launch and Orbital Operations Support. The CER for Integrated Assembly and Checkout has the same form with the exception that the independent variable is total Systems Test Hardware cost.

Systems engineering uncertainty is accounted for by first calculating the 10^{th}, 50^{th}, and 90^{th} percentiles for each of the total hardware DD, Flight Unit, and STH cost distributions. Each CER is calculated three times using the appropriate hardware cost, yielding a low, a most likely, and a high value that are used to define a triangular distribution. These values are defined as:

$$\textit{Low} = a(10^{th}\ \textit{Percentile Hardware Cost})^{b} \tag{65}$$

$$\textit{Most Likely} = a(50^{th}\ \textit{Percentile Hardware Cost})^{b} \tag{66}$$

$$\textit{High} = a(90^{th}\ \textit{Percentile Hardware Cost})^{b} \tag{67}$$

The CER standard error distribution is then added to the triangular using the method of moments, and approximated by a lognormal. This is the same method used to define uncertainty distributions for hardware element costs. Note that the uncertainty for systems engineering is directly tied to the hardware uncertainty. However, because analytic approximation does not account for this functional correlation in its calculations, we must add it. The default correlation value between each hardware element and each systems engineering element is 0.2. Also, the default correlation value between any two systems engineering elements is 0.2.

The method of moments is then reapplied to all WBS elements to yield top-level means and variances, again taking correlation into account.

Risk Results

The next step is to postulate that the total-cost mean and standard deviation are the mean and standard deviation, respectively, of the total cost lognormal distribution. We use the formulas from a previous section to calculate P and Q to determine the mean and standard deviation of the normal distribution that underlies the total-cost lognormal distribution.

After we know the numerical values of P and Q we then calculate the "icosotiles", namely the 5^{th}, 10^{th}, …, 95^{th} percentiles, of the total-cost lognormal distribution using an e-version of the tables of the standard normal distribution along with the formula from Section 2 that asserts

$$(1-\alpha)\text{th percentile} = eP+z\alpha Q\ . \tag{68}$$

NAFCOM also offers the analyst the opportunity to approximate the total-cost distribution by a normal, rather than a lognormal distribution. According to statistical theory, the normal distribution should provide a better approximation to a statistical sum of triangular distributions than would the lognormal distribution under the following three circumstances: (1) There is a large number of WBS elements, so that the Central Limit Theorem of statistics applies; (2) The triangular distributions are not very skewed, so that convergence of their sum to the (symmetric) normal distribution does not require very many WBS elements; and (3) There is little or no correlation between WBS elements, so that each WBS element contributes fully to the statistical sum, thereby achieving acceptable convergence with a smaller number of elements. The normal approximation has been recommended by W.P. Simpson and K.P. Grant in their 1994 Air Force Institute of Technology technical report, "An Investigation of the Accuracy of Heuristic Methods for Cost Uncertainty Analysis," the essential points of which were recently published in *The Journal of Cost Analysis &*

Management (Winter 2001, pages 1-18.). The icosotiles of the total-cost normal distribution would be simply the numbers $P+z_{\alpha}Q$, where P and Q are calculated just as described above.

NAFCOM Risk Inputs

NAFCOM CER analysis is performed at the subsystem level – structures, electric power, thermal control, etc. The air breathing support equipment, avionics, miscellaneous hardware, and range safety CERs are single-variate. For these CERs, the only independent variable is weight. The user can select low, most likely, and high values for the weight inputs. The NAFCOM rocket engine CER is Boeing's Liquid Rocket Engine Cost Model (LRECM). For this version of the model, the user is not able to select low, most likely, and high values for any of the inputs for LRECM. Thus, risk is not included for the engine subsystem. However, the user has the option of choosing a weight-based CER for engines (where weight is the only independent variable). For this "conventional" CER, the user inputs low, most likely, and high values for the weight. For the remaining subsystems, the user has the option of using a single independent variable CER (weight), or the user can make use of NAFCOM's complexity generators. For the "conventional" CERs, the user may select a low, most likely, and high value for weight.

NAFCOM complexity generators are multi-variate CERs. They have the general form:

$$Cost = a * Weight^{b1} * New\ Design^{b2} * Technical^{b3} * Management^{b4} * Class^{b5}, \qquad (69)$$

where "New Design" is the percentage of new design for the mission; "Technical" represents the technical rating, and is based on a number of technical factors and is subsystem dependent; "Management" represents the management inputs and is based on six factors: manufacturing management complexity, funding availability, test approach, integration complexity, engineering management complexity, and amount of pre phase C/D work done; and "Class," which represents the mission class: unmanned earth orbiting, unmanned planetary, launch vehicle, and manned. There are some other independent variables included in various CERs, but the above equation represents the basic form.

The NAFCOM risk inputs allow the user to set low, most likely, and high values for almost all NAFCOM complexity generator inputs for each subsystem – e.g., weight, test approach, power output. The risk inputs for the complexity generators vary by subsystem – see Table 15-1 through Table 15-14 for a complete list.

Table 15-1 - Attitude Control Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Computer (Yes/No)
Engineering Methods	Horizon Sensors (Yes/No)
Manufacturing Management	Sun Sensors (Yes/No)
New Design	Radar Altimiter (Yes/No)
Funding Availability	Star Trackers (Yes/No)
Risk Management	Gyros (Yes/No)
Pre-Development Study	Magnetometers (Yes/No)
Integration Complexity	Rendezvous Radar (Yes/No)
Redundancy	Stabilization Method
	Autonomy

Table 15-2 - CCDH Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	CC&DH Type
Engineering Methods	Frequency Bands
Manufacturing Management	Number Transmitters
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	
Redundancy Rating	

Table 15-3 - ECLS Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Long Term Orb. Env. (Yes/No)
Engineering Methods	Environment
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	
Crew Size	
Mission Duration	
Volume	

Table 15-4 - Crew Accommodations Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Environment
Engineering Methods	
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	

Table 15-5 - Electric Power Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Power Regulation
Engineering Methods	
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	
Output Power	
Storage Capacity	
Design Life	

Table 15-6 - Landing Gear Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	
Engineering Methods	
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	

Table 15-7 - OMS Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Environment
Engineering Methods	Reusability
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	

Table 15-8 - Propulsion Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Environment
Engineering Methods	Reusability
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	

Table 15-9 - Reaction Control Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Propellant Type
Engineering Methods	
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	
ISP	
Thrust	
Propellant Weight	

Table 15-10 - Recovery Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	
Engineering Methods	
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	

Table 15-11 - SRM/AKM Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Retrorocket (Yes/No)
Engineering Methods	Upper Stage Only
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	
Total Impulse	

Table 15-12 - Structures Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Large Inert Structure(Yes/No)
Engineering Methods	Number of Deployeds
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	

Table 15-13 - Thermal Control Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	Louvers/Heaters (Yes/No)
Engineering Methods	Special Materials (Yes/No)
Manufacturing Management	External Cryogenic Storage Tank (Yes/No)
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	
Design Life	

Table 15-14 - Thrust Vector Control Complexity Generator Inputs

Included in Risk Calculations	Excluded from Risk Calculations
Weight	
Engineering Methods	
Manufacturing Management	
New Design	
Funding Availability	
Risk Management	
Pre-Development Study	
Integration Complexity	

See Figure 15-2 for the Structures input screen.

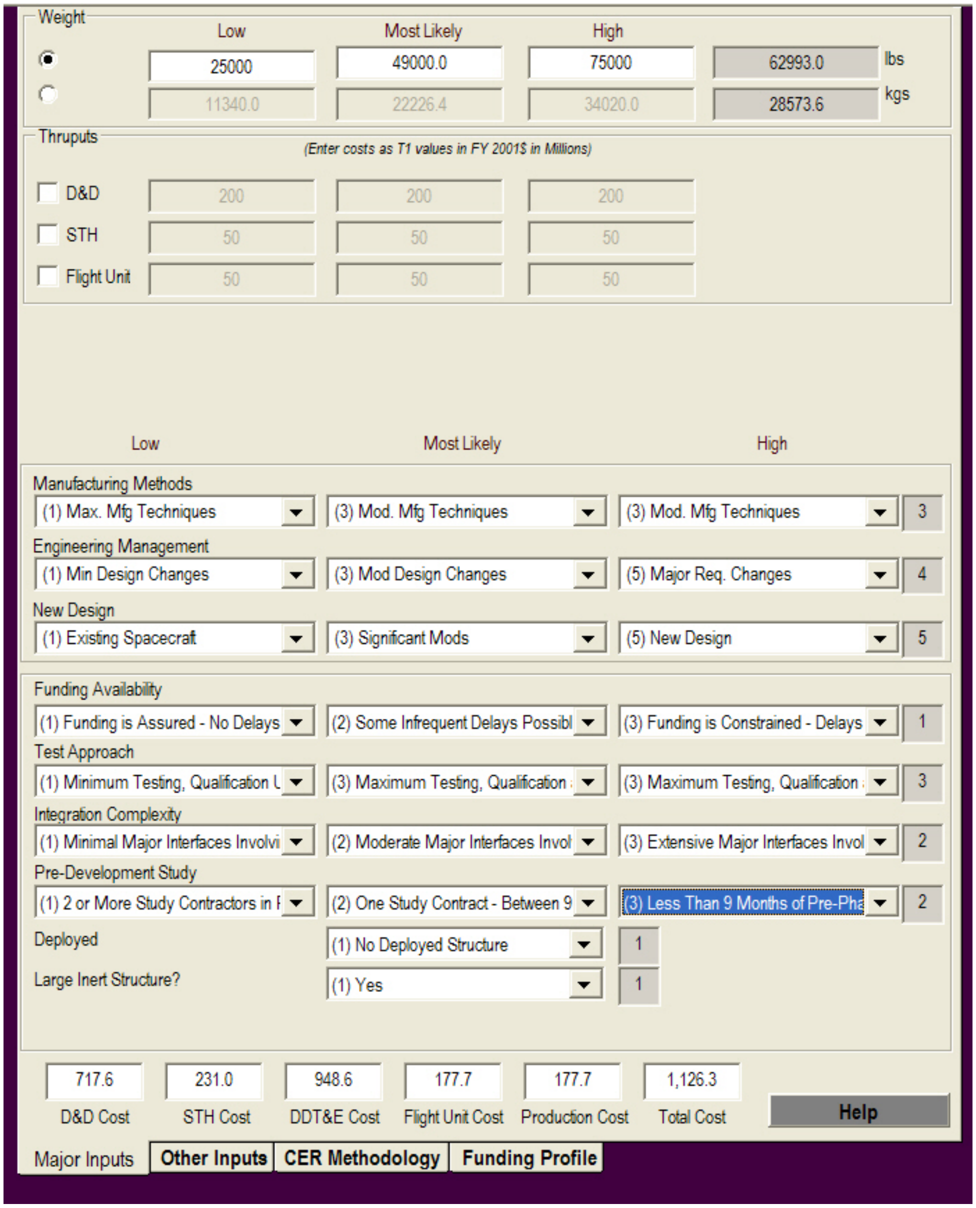

Figure 15-2 - Input Screen for Structures Subsystem

The user chooses low, most likely, and high values for each CER input – weight, manufacturing methods, engineering management, percent new design, funding availability, test approach, integration complexity, and amount of pre-development study. Two inputs – number of deployed structures and whether or not the structure is a large inert structure (such as the External Tank or the Solid Rocket Boosters), are decided early enough in a program that they are assigned no technical risk.

Once the low, most likely, and high inputs have been entered, the user clicks the “Run Risk” button to begin the risk analysis calculations. The user is asked whether he/she would like to edit the correlation matrix. If the user declines to edit the matrix, the calculations are performed and the results are displayed. If the user decides to edit the correlation matrix, the DDT&E correlation matrix is displayed, which the user can then set to any value between -1 and 1. See Figure 15-3. The user can edit both the DDT&E and

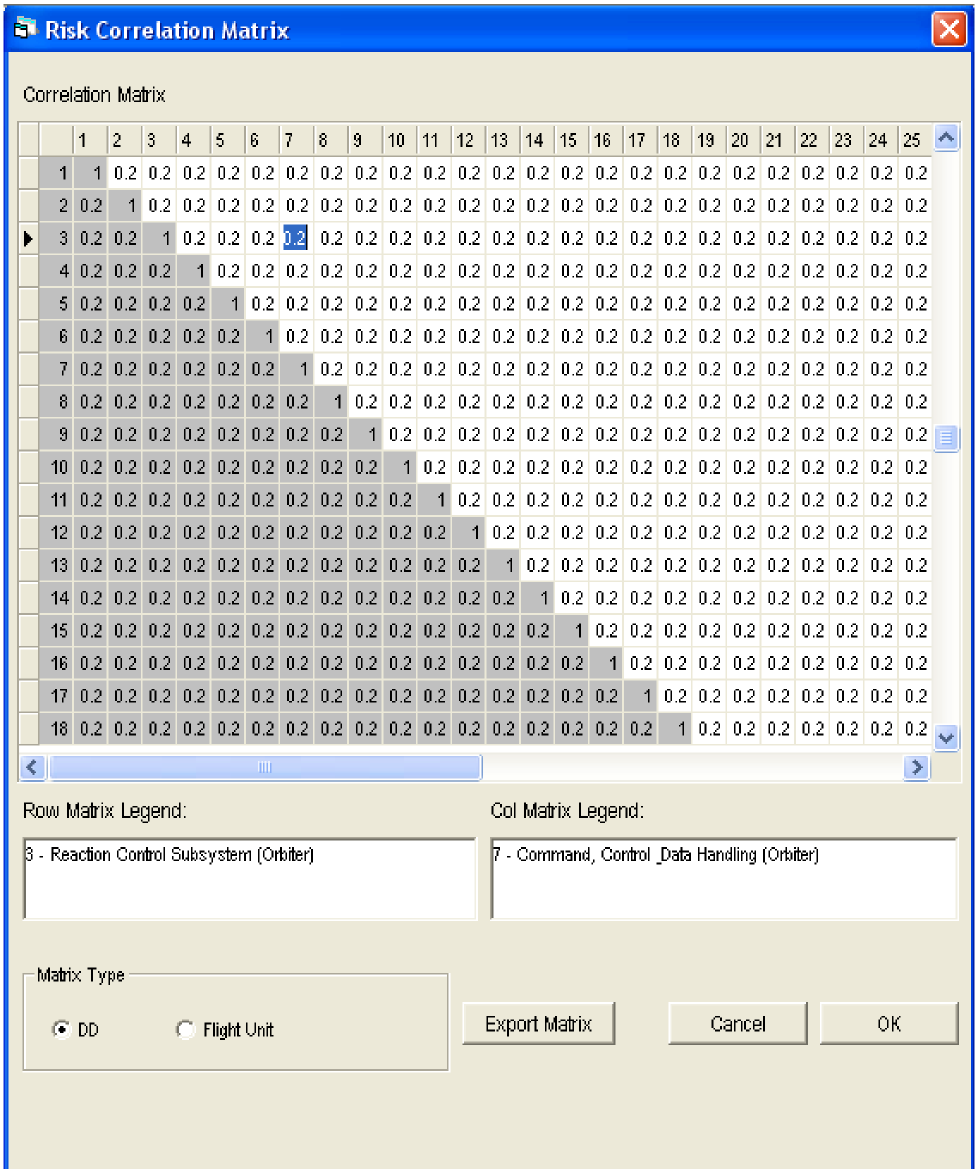

Figure 15-3 - NAFCOM Correlation Matrix

flight unit correlation matrices. The user can also export the matrices to Excel if desired. Once the user has finished editing the correlation matrices and clicks the “OK” button, the risk analysis the calculations are performed and the results are displayed.

NAFCOM Risk Outputs

The NAFCOM risk analysis outputs consist of statistics, graphs, and reports. For DDT&E, Flight Unit, Production, and Total Cost, NAFCOM prints a table consisting of the mean, median, mode, standard deviation, coefficient of variation, and the 5th and 95th percentiles, and every 10th percentile from the 10th to the 90th percentile. The graphical display consists of the probability density function (PDF) and the cumulative distribution function (CDF) for the lognormal (or normal) distribution for the DDT&E, Flight Unit, Production, and Total Cost at each of the subsystem hardware, stage, and total levels. See Figure 15-4 and Figure 15-5.

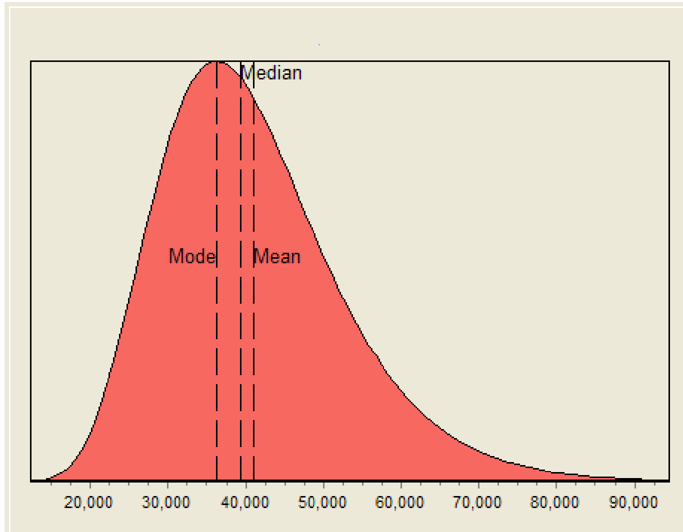

Figure 15-4 - Lognormal PDF for the Total Cost Distribution

	DDTE	FU	Total
Mean	25715.1	15364.6	41079.7
Median	24008.7	14716.1	39411.3
Mode	20928.1	13500.1	36275.1
s	0	4611.3	12078.8
5th	13051.3	9078.3	24542.4
10th	14932.1	10100.5	27249
20th	17576.1	11493.5	30929.2
30th	19768.5	12615.7	33887.5
40th	21857.3	13660.9	36638.5
60th	26371.9	15852.8	42394.1
70th	29158.4	17166.3	45835.5
80th	32795.7	18842.4	50219.7
90th	38602.7	21441	57002.1
95th	44165.8	23855.1	63288.6

Figure 15-5 - Statistics Display for DDT&E, Flight Unit, and Total Cost Distributions

Other Features

An additional feature in the latest version of NAFCOM is the ability the ability to determine which elements have the most cost risk associated with them by allocating risk dollars back to those WBS elements. The user selects a percentile (70th, 80th or 90th) to be used to determine the amount of risk dollars to be allocated to the WBS elements. The method used is the same as the one described in the section “Allocating Risk Dollars back to WBS Elements.”

16. PRICE Systems Family of Models

Jim Otte
PRICE Systems

Overview of Risk

PRICE H and PRICE S have been designed to play a critical role in both cost and schedule analysis. The risk analysis facility in the PRICE Models enables you to translate the uncertainty in the proposed hardware or software system's parameters to an assessment of cost and schedule risk. Risk can be run on the entire Equipment Breakdown Structure (EBS) or on a single element within the EBS. The risk analysis process should include five basic steps:

1. Structure the EBS for the hardware or software system so that high risk elements can be identified.
2. Determine the most uncertain input parameters for those elements.
3. Quantify the uncertainty for each parameter in each element chosen.
4. Perform a simulation.
5. Evaluate the results and iterate if required.

Input Requirements

Point – a point represents the most likely value for the parameter. It is entered as the single value on the PRICE H/S Input Screen. However for those parameters the analyst feels uncertain about, or when low and high values for that parameter are provided by engineering or program office personnel, a Risk Analysis should be considered. These Point Inputs can be quantified for uncertainty on the Risk Input screen by percentage (%), a delta change (D), or a numeric value (#) when entering the minimum and maximum values. The percentage, delta and number selections have no affect in Normal Distribution.

Iterations – specifies the number of separate runs or passes through the EBS, assembly or element. Each run will select a random value within the range and distribution of each input parameter. The default is 1,000, however, it will accept as few as 25 iterations or as many as 8,000 iterations.

Seed – is a number used to initialize the Random Number Generator for the simulation. Enter any whole number from zero to 10,000. The default is one (1).

Monte Carlo and Latin Hypercube – are options for the simulation sampling technique of risk analysis. Both techniques are suitable for high numbers of iterations, but Latin Hypercube has some advantages when working with a low number of iterations. A more detailed explanation of the two techniques is available in the Your Guide to PRICE H or PRICE S manual.

Distribution – selects the general shape for graphic display of probability distribution function. There are four types of distributions available for use in PRICE H/S Risk Analysis:

Normal – values are symmetrical about the mean; a bell curve.

Beta – asymmetrical, marked by cluster around either a low or high value.

Triangular – while not exact, the easiest to use for analysts; very versatile.

Uniform – any value between the minimum and maximum is equally likely.

Minimum, Point, Maximum, StdDev, Alpha, Beta—these inputs may be required depending upon which distribution is selected. Those that are required are in the un-grayed areas. Those not needed are displayed in gray. More detail on each of these inputs is available in the Your Guide to PRICE H or PRICE S manual.

Operations

Model Operation

Risk Analysis may be accomplished at the system level (all EBS items), the assembly level (all elements indented below the assembly), and the element level (one EBS element).

If risk analysis is performed at the system level, PRICE H/S will make as many runs as specified through the EBS, randomly sampling any and all specified input distributions. Each pass through the EBS will result in a total cost estimate for the system. If 1,000 iterations are requested for a hardware or software system, PRICE H/S will make 1,000 separate system estimates.

For risk analysis at the assembly level, PRICE H/S will make iterations on the selected assembly only. Certain EBS elements can be designated as dependent on the next higher element.

Risk input distributions may be input at an element level, or rippled down to the element level from the system or assembly level. During this ripple, any of the assembly or individual element variables can be Locked to prevent their current input distributions from being altered.

If risk analysis is performed at a hardware element level, PRICE H/S will make as many runs as specified on the selected element, randomly sampling any and all input distributions. Each pass through the particular element will result in a total estimate for only that element.

For variables that do not have any risk input distribution specified, their single input value will be used for each iteration.

Parameters with an input value of zero keep their zero value even if a risk distribution is specified.

Output Results

Graphic—Results are graphically displayed on the screen and can be saved, cut and/or pasted into other windows applications such as a word processor.

Formatted Reports—Results are also presented in three formatted reports which can be viewed on the screen, saved to a file, or printed to a local or network printer.

Output Files—Results can be exported to most popular applications.

Risk Input Screen

The following definitions refer to those inputs entered in the Risk Input screen.

Min – refers to the lowest possible value for the parameter being evaluated. It represents the lowest foreseeable or estimable value for the distribution in question. However, in all distributions except Uniform, the probability of its occurrence is so low it approaches zero. In the Uniform distribution, the Minimum has the same probability of occurrence as the Point or the Maximum. This input is required for the Beta, Triangular, and Uniform distributions only.

Point – is the value that is most likely to occur. It is sometimes referred to as the Mode, which is the value that occurs most frequently in a distribution. The term Point refers to the value you would use in PRICE H/S for a deterministic, single point estimate. A point estimate of the parameter in question is required for all distributions. The point value from the PRICE H/S Input Sheet screen is automatically transferred to the Risk Input screen and shown in subdued gray. These point values can only be changed in the Input Sheet of the element. A zero point value is not valid for distribution.

Max – is the highest possible value for the distribution. It represents the highest foreseeable or estimable value for the parameter in question. However, in all distributions except Uniform, the probability of its occurrence is so low it approaches zero. In the Uniform distribution, the Maximum has the same probability to occur as the Point or the Minimum.

Std Dev – refers to a measure of the dispersion of values about the mean of a probability distribution. It is only required when the Normal distribution is selected.

Alpha – is a parameter only used for the Beta distribution. Alpha together with Beta describe the peakedness of the distribution versus its skewness. Alpha must be greater than 1.0 and less than 99.9.

Beta – is a parameter only of the Beta distribution. Beta, together with Alpha, describe the peakedness of the distribution versus its skewness. Beta must be greater than 1.0 and less than 99.9.

Risk Analysis Output

Graphical

a) Cumulative Distribution Function—This graph displays cost as a function of the cumulative probability of under-run on the left Y-Axis from zero to 1.0 or 100%. It also displays cost as a function of the cumulative probability of over-run on the right Y-Axis from 1.0 or 100% to zero. This graph is sometimes referred to as a probabilistic cost estimate. See the section on Analyzing Results for a more complete discussion of this graph.

b) Probability Distribution Function—This graph displays the number of samples within each cost range of the X Axis, and the number of iterations that particular cost was calculated on the Y Axis.

c) The Options button displays a pop-up screen of distribution display options. You can change the number of ranges displayed or the starting and ending points of either the X or Y Axis. Also, you can toggle the display from the default Total Cost to either Development or Production Cost or Schedule length. The type of graph can be changed from a Cumulative Probability Function to Probability Distribution Function.

d) The Statistics button displays a pop-up screen of the important statistical measures of the simulation just performed. The definitions of these statistics are given below again for completeness.

Export

Export allows you to export the input and output for the current simulation to a file. Click on the Export button. An Export Risk File As screen will appear. The default save file type is Distribution Files or .rsk file type. This allows you to name the file to be viewed via the View Simulation button on the Format Reports screen. (This is the only way you can view the .rsk file.) The other type of file can be selected via the arrow button. Selecting "CSV Distribution Files" will create an output containing both the risk variable input and output values used in each run of the simulation. This .csv file can be viewed as a spreadsheet in EXCEL.

17. SEER

Dan Galorath and Karen McRitchie
Galorath, Inc.

Introduction

SEER-SEM is one of cost models in the SEER family of models produced by Galorath Inc. The fundamental risk calculations shown for SEER-SEM are the same as for SEER-H and SEER-DFM with exceptions as noted.

SEER-SEM forecasts outcomes. In forecasting, no single number can represent the future; only a range of probable future outcomes can. Ranges are a natural result of the uncertainty in your inputs – recall that most parameters are entered in a Least, Likely, Most format.

It is unrealistic to expect absolute certainty about future outcomes. So, imagine instead, as is normally the case, that you are not absolutely certain of your inputs. You have specified each parameter as a range, from least likely to most likely. SEER-SEM uses these inputs to form probability distributions, which are then sent through its calculation functions as seen in Figure 17-1:

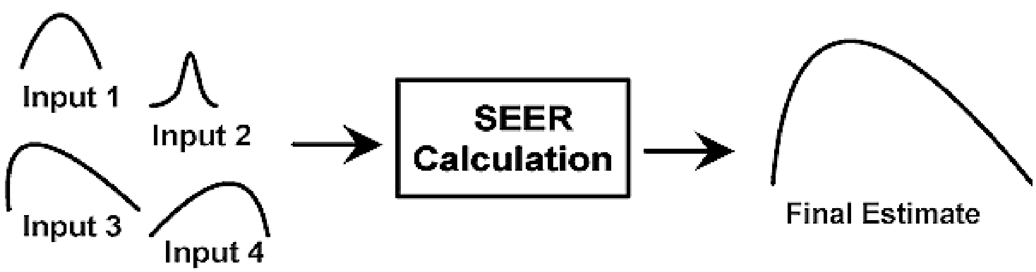

Figure 17-1 - Basing final estimate uncertainty on input uncertainties

Since there is uncertainty in your parameter inputs, there will be a range of possible outcomes in the resulting estimate. This is natural and good, for an estimate range allows you to make more informed risk-based project management decisions.

Operations

Risk at the Parameter Level

Estimates of size and of technology parameters expressed as single point values don't tell the whole story:

- How confident am I in this value; i.e., what is the probability of not exceeding this value?
- How certain am I in this value; i.e., how wide is the range (probability distribution)?
- Three-point estimates are better:
- Least: "I can't reasonably imagine the result being any smaller than this."
- Likely: Best Guess; "If I were forced to pick one value, this would be it."
- Most: "I can't imagine the result being any larger than this."

Every potentially uncertain SEER-SEM parameter accepts three-point estimates (has three inputs), such as these for the pre-existing lines of code parameter:

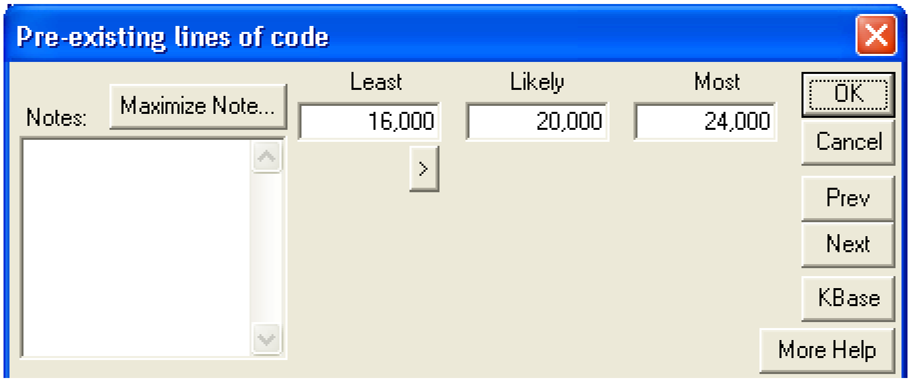

Figure 17-2 - Input distribution dialog box

SEER-SEM uses these inputs to construct a Pert (generalized beta) distribution. Pert distributions are quite common in risk analysis work because they are intuitive and easy to work with. They are similar to normal distributions and can be described using the values of a three-point estimate.

Parameter-Level Risk Distribution

For each risk-based SEER-SEM parameter, a separate Pert distribution is generated using its three inputs. The traditional Pert distribution has the following characteristics:

$$Mean = \frac{(Least + 4 \times Likely + Most)}{6} \tag{70}$$

$$\sigma = \frac{Most - Least}{6} \tag{71}$$

For a SEER-SEM estimate where the desired probability is set to 50% (the default), the Pert mean is used. At desired probabilities other than 50%, the Pert mean and derived standard deviation (σ) are used to compute the appropriate value for the desired probability.

The traditional Pert assumes all points are distributed symmetrically about the mean. Because input ranges are not necessarily symmetric, intuition implies that outputs should not be symmetric either. To consider the possible skew expressed in the Least, Likely, and Most input range, SEER-SEM uses a modified standard deviation:

$$Right\sigma = \frac{Most - Mean}{3} \tag{72}$$

$$Left\sigma = \frac{Mean - Least}{3} \tag{73}$$

When the Least and Most inputs are symmetric about the Likely input, this modified Pert is equivalent to the traditional Pert.

Risk at the Program Element Level

We have established that parameters are assigned probability distributions. These parameter distributions are then fed into the SEER-SEM model to produce a range of estimates. The more inputs vary, the greater is the variation in estimated outcomes, as shown in Figure 17-3:

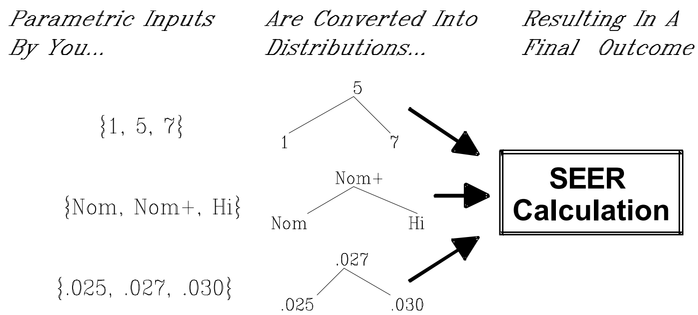

Figure 17-3 - Conversion of parametric inputs to distributions

The key to the above distributions is variation in the Least, Likely and Most inputs. If there were no variation in inputs, then the parameter distributions above would all be vertical lines (no width). The resulting estimate would be a SURE THING—estimates at 1%, 99% and everything in between would be the same. The more inputs vary, the greater is the variation in the estimated outcome.

Calculating a Specific Probability

Recall that all parameters with Least, Likely and Most inputs have a Pert distribution. With distributions specified by your inputs, values at any probability level can be obtained. Imagine that an estimate is desired at the 40% level (more later on how to set this). SEER-SEM will obtain the estimate by doing the following:

1. All parameter distributions are sampled for their value at the 40% level.

2. These values are passed through the SEER estimating machinery.

In general, all parameters are sampled at the same probability level—this is equivalent to project factors being fully correlated.

Setting The Probability

In most SEER reports, estimates are given as specific numbers, meaning that a specific probability level must be chosen. This level is set using the Effort Probability and Schedule Probability parameters found in every Program element parameter list under the heading Confidence Level.

- CONFIDENCE LEVEL
    - Effort Probability 50.00%
    - Schedule Probability 50.00%

The default setting for these probability inputs is 50%, meaning if you were to run this project 100 times, fifty times you would see effort values less than the predicted value and fifty times you would see effort values greater than the predicted value (the same is true for schedule). You can adjust each of the two desired Confidence Level probability parameters (Effort Probability and Schedule Probability) to correspond with the amount of risk the project can tolerate. In other words, if it is critical that the project satisfy its effort commitment, its schedule commitment, or both, then these commitments should be based on a solution that has high confidence percentages. If, on the other hand, it is not critical that these commitments be met (or if the benefit of success grossly outweighs the cost of failure), then these commitments could be based on a solution that has lower confidence percentages.

Confidence Level probabilities may be set differently for each Program element, so you can use a mix of probability settings. You might, for example, want to specify conservatively high probability levels for the most critical elements in a program.

Setting probability differently in different parts of a project can have a significant impact. At worst, your project components will be inconsistent and thus not comparable. Make certain that you carefully document your ground rules and assumptions before doing so.

The Confidence Tuner may be used to interactively set the effort and schedule probability inputs. The Confidence Tuner can be invoked from the toolbar or the risk charts by clicking on the button.

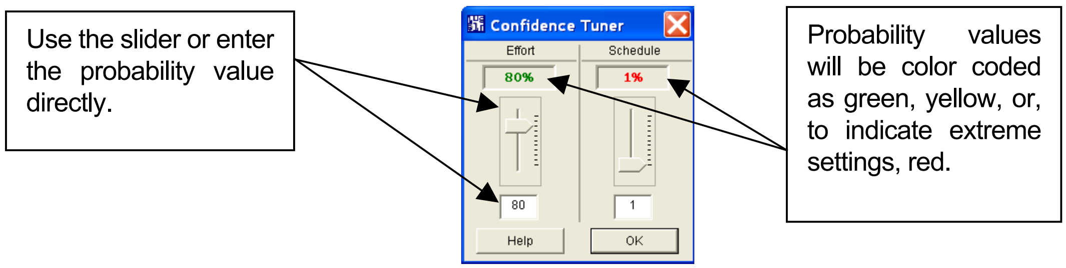

Figure 17-4 - Confidence Tuner

Detailed Risk Inputs – the Risk Tuner

SEER-SEM enables you to fine tune your risk analysis even further with the Risk Tuner, which allows you to rate the risk levels for specific categories of inputs. The risk tuner is invoked by clicking on the button.

The risk tuner can be used to isolate the impact on the estimate for a subset of parameters. As an example, you might want to evaluate the impact of your size input ranges on your estimate while keeping everything else constant. You can use the Risk Tuner for this.

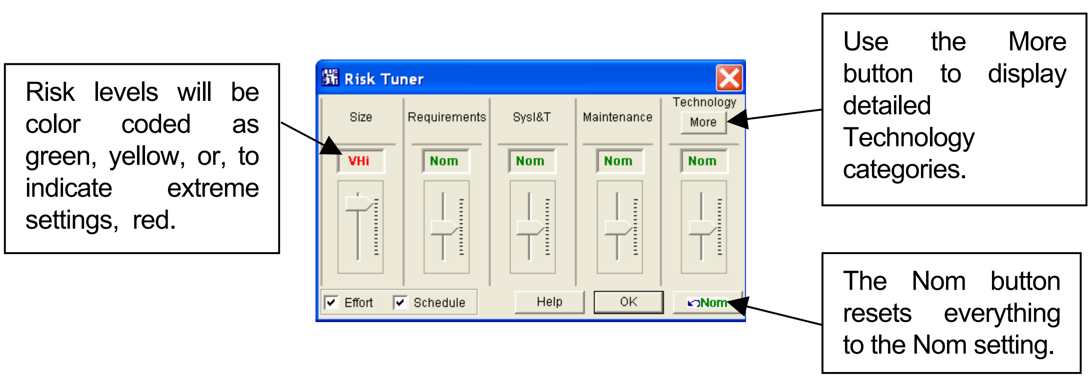

Figure 17-5 - Risk Tuner

You can expand the Risk Tuner to reveal more detailed parameter categories by clicking on the More button in the Technology risk column. This will display adjustable risk inputs for each of the technology and environment parameter categories.

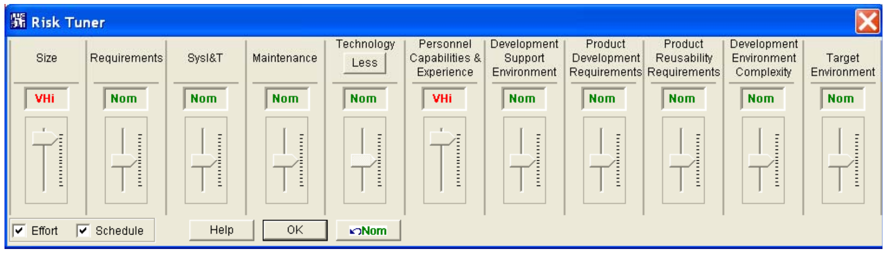

Figure 17-6 - Expanded Risk Tuner

The detailed Risk Tuner settings range from Very Low - to Very High +. The higher the setting, the more risk is incorporated into your estimate, yielding a higher cost and/or longer schedule.

Risk-Based Program Element Level Charts and Reports

SEER-SEM includes a detailed Risk Analysis report and five Risk charts, which present a range of estimate outcomes at the Program element level. Charts are available for effort, schedule, cost, benchmark vs knowledge base, and defects risk:

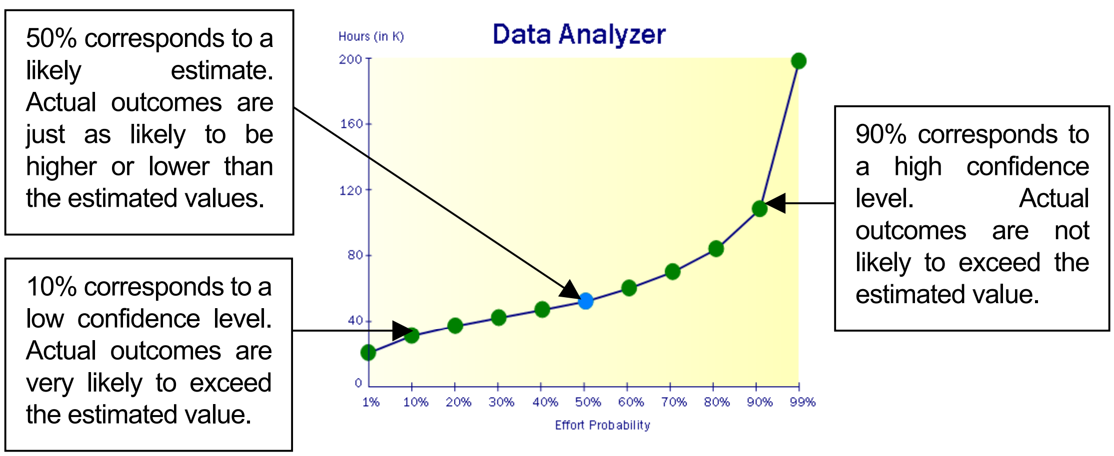

Figure 17-7 - Data Analyzer

The Risk Analysis report provides details on schedule, effort, and cost:

Table 17-1 - Risk Analysis Output

SEER-SEM (TM) Software Schedule, Cost & Risk Estimation Version 7.0.24

Project : Watcher 11/10/03
Program : 1.1: Data Analyzer 1:41:36 PM

Risk Analysis

Development					Maintenance	
Probability	Sched Months	Effort Months	Effort Hours	Cost	Effort Months	Cost
1%	19.76	135.05	20,527.30	2,309,322	0	0
10%	22.78	204.25	31,045.92	3,492,666	0	0
20%	24.17	243.50	37,011.58	4,163,803	0	0
30%	25.22	276.65	42,051.42	4,730,785	0	0
40%	26.16	308.80	46,936.94	5,280,406	0	0
50%	27.07	342.51	52,060.84	5,856,845	0	0
60%	28.32	394.98	60,037.00	6,754,163	0	0
70%	29.72	460.59	70,009.73	7,876,094	0	0
80%	31.43	552.08	83,915.57	9,440,502	0	0
90%	33.95	711.08	108,084.40	12,159,495	0	0
99%	40.76	1,302.89	198,038.92	22,279,379	0	0

Risk at the Project/Rollup Level

Until this point, owe have considered risk analysis at the individual Program element level. Now we look at risk analysis for multiple Program elements. The Project/Rollup Risk Calculation uses a special technique known as Monte Carlo sampling to give statistically valid estimates at the project and rollup level. By **sampling program elements,** randomized Program-element-level samples are obtained and accumulated. "Randomized" means that any estimate from 1% to 99% is equally likely to occur.

Cost and schedule estimates from each Program element are totaled against estimates from every other Program element. Each set of accumulated estimates constitutes one sampling.

This process is iterative. The total sample must be suitably large for accurate final statistics, so the above steps are repeated a large number of times.

A larger sample means more information and more accurate sample statistics, but a longer Project/Rollup Risk Calculation. Set the number of iterations (sample size) in the Project Parameters dialog box to get the best balance between time and accuracy for your project.

Monte Carlo Analysis for Schedules

SEER-SEM applies the Monte Carlo method to schedule analysis in a somewhat different manner than does cost. For each sampling iteration, the program computes an elapsed schedule for the project or rollup, running from the earliest stated start date to the latest estimated ending date. If all Programs have the same start date, the elapsed schedule will equal the longest schedule of any individual Program. Once all iterations are complete, the program takes statistics from this set of newly generated, longest-possible schedules. The 50% confidence level represents the median of this sample.

The chart below provides an example. Each Program (A, B, and C) has a generated schedule outcome. The project schedule for each iteration is determined by the longest elapsed schedule generated for a Program in that iteration. The project median schedule is computed from this sample set.

Iteration	Sample of Program Schedules A	B	C	Project Sampling
1	9.36	3.04	4.39	9.36
2	13.74	10.77	14.46	14.46
:	:	:	:	:
:	:	:	:	:
:	:	:	:	:
99	5.94	18.70	15.64	18.70
100	4.25	15.80	3.56	15.80
Median	7.65	13.29	9.43	15.13

Longest schedule of the sample across Programs*

Median of the longest schedules

Median program schedule derived from the sampling

* assumes that all start dates are the same. If they are different, the Project Sample for that iteration would be the longest elapsed schedule.

Figure 17-8 - Monte Carlo schedule analysis

Correlation among Program Elements

Correlation is the extent to which two variables vary together. In Monte Carlo sampling, the notion of correlation among Program elements is important. SEER-SEM offers both fully correlated and fully uncorrelated estimates.

The fully uncorrelated estimate is marked as "Independent" on the risk report. It also appears on the risk charts. The "Independent" case implies that the computer programs (WBS elements) in your project are essentially independent of one another and the outcome of one program will not impact the outcome of another program. In other words, if things go badly for one program, there will be no negative impact on other programs being evaluated.

The fully correlated estimate is marked as "Dependent" on the risk report. The "Dependent" case implies that the computer programs (WBS elements) in your project are interrelated and the outcome of one program will certainly impact the outcome of another program. In other words, if things go badly for one program, things will also go badly for the other programs being evaluated. The risk estimates for the dependent case tend to be more extreme than for the independent case. They are usually higher at the 90% confidence and lower at the 10% confidence level than for the independent case.

For partial-correlation outcomes, interpolate between the full- and zero-correlation cases.

Results

Risk-Based Project/Rollup Level Charts and Reports

The risk-based reports and charts available at project and rollup levels in SEER-SEM are:

Charts

- Cost Risk
- Schedule Risk

Reports

- Project/Rollup Cost Risk
- Project/Rollup Schedule Risk

Charts

Following is a project/rollup risk chart. This type of chart is typical at the Program element level; however, it is only supported at higher levels of indenture when the Project/Rollup Risk Calculation is enabled.

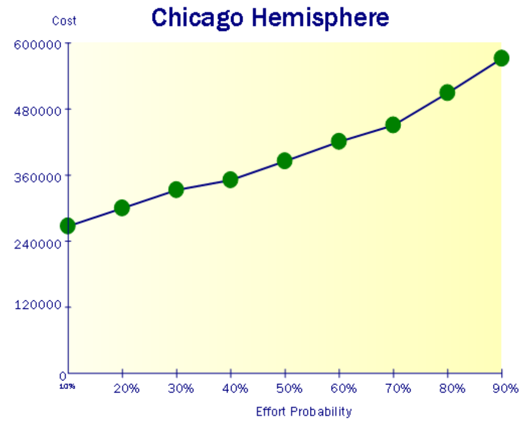

Figure 17-9 Project/Rollup Risk Chart

At the rollup level, a few things are worth noting about this and other risk charts:

- Risk charts assume that Program outcomes are fully independent.
- Amounts are being summed, and so they may be much higher in project- and rollup-level risk charts than in lower-level WBS elements.
- The distribution of outcomes along probability intervals may be somewhat more irregular (or asymmetric) than the distribution at the Program level. This is because Programs may have very uneven cost or schedule impacts.

Reports

SEER-SEM offers cost and schedule risk reports at the project and rollup levels. These reports offer more information than the risk charts:

- Cost and schedule estimates are given for both fully independent and fully correlated Program outcomes, allowing you to infer partially correlated results.

The 50%-level outcome also is apportioned to individual Programs according to each one's cost—or schedule—share of the total sample. This is useful when a project/rollup risk estimate must be allocated to subordinate Programs, as shown in Table 17-2 - SEER WBS allocation report.

Table 17-2 - SEER WBS allocation report

```
                              Project/Rollup Cost Risk

Confidence Level         Dev Cost (Independent)     Dev Cost (Dependent)
________________         ______________________     ____________________

      10%                               266,925                  197,560
      20%                               299,619                  239,802
      30%                               332,724                  278,610
      40%                               350,772                  319,496
      50%                               385,349                  353,122
      60%                               420,530                  403,324
      70%                               450,560                  474,750
      80%                               509,112                  551,974
      90%                               571,766                  678,776

 (Based on 100 iteration sampling)

                                       WBS Allocation Of Most Likely Development Cost

                                         Dev Cost      % of Total       (StdDev)
                                       ____________    __________     _____________

+ 1.2: Chicago Hemisphere                   385,349                   (    124,770 )
   - 1.2.1: Prices Database                 205,522        53.33%     (    103,357 )
   - 1.2.2: Intranet Library (Perl)          92,293        23.95%     (     56,474 )
   - 1.2.3: Report System                    87,534        22.72%     (     44,573 )
```

A Note on Accuracy

Given a specific probability, every point on the risk charts or reports represents the *most probable* value. This is represented graphically by a *confidence interval* around each point. An intuitive explanation of a confidence interval is “the band within which most outcomes will occur.” Only the midpoints of confidence intervals are shown on risk charts.

With more iterations in the project/rollup risk calculation, there is more information, and so confidence intervals will narrow.

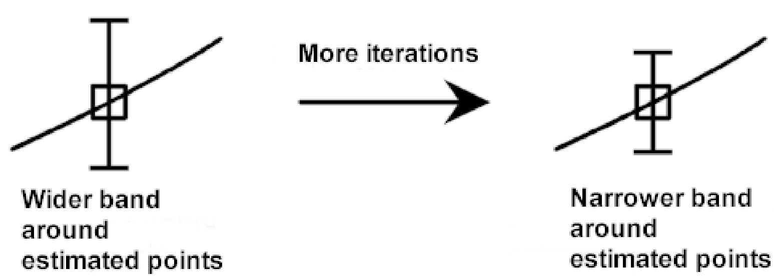

Figure 17-10 - Confidence Intervals

As the interval of most probable outcomes narrows, the corresponding midpoints may shift.

18. Small Satellite Cost Model (SSCM)

Greg Richardson, Melvin A. Broder, and Eric Mahr
The Aerospace Corporation

Introduction - Modeling Cost Uncertainties

One of several dilemmas in cost-estimation is the "normal" uncertainty inherent in parametric models, comprised of such things as uncertainty associated with hardware design, inflation, labor rates, contractor accounting practices and overhead rates. In the case of parametric cost models utilizing general-error regression, and with SSCM in particular, general cost-estimating uncertainty is quantified by the standard error of the estimate (SEE). SEE quantifies the accuracy to which the cost model represents its own underlying data under the various uncertainties.

Another source of cost risk, growth due to unforeseen technical difficulties, has perhaps even greater potential to cause costing uncertainty than any other single influence. These technical difficulties are related to a program's attempt to inject new technologies with limited or no previous flight demonstration into the design of the spacecraft. Twelve major NASA programs initiated after 1977 and completed before 1993 experienced an average cost growth of 77%, with eight of them citing technical complexities as a major risk driver [1]. Unfortunately, quantification of technical risk is not nearly as straightforward as quantifying general cost-estimating uncertainty.

Previous versions of SSCM implemented a scheme for dealing with technical difficulties by using NASA Technology Readiness Levels (TRLs). This scheme adjusted the CER-generated cost estimate based on the technological maturity of each subsystem as defined by the user using triangular cost probability distributions for each cost estimate. This required a number of assumptions to be made: cost savings due to proven technology, cost additions due to unproven technology, and the average technology level on which to base the adjustment. Baseline assumptions were provided in the model, but due to uncertainty in what the "correct" values of these assumptions were, the user was provided the opportunity to change how technology readiness modified the estimate.

The level of design reuse (i.e. heritage) in a particular subsystem design also impacts the amount of cost risk inherent in building that subsystem. Heritage is not the same as technical difficulties – one can have a system where a previously developed design is utilized, but new technologies are also being incorporated. A common example is a bus that utilizes an existing ADCS design, but incorporates a new set of sensors (e.g. star tracker) into a standard interface. Previous versions of SSCM also provided an adjustment to the cost due to the heritage level of a particular subsystem. The algorithm that was used moved away from other cost models that simply assume that the CER estimate contains no heritage and scaling the estimate. The user was provided the opportunity to input the heritage level for the subsystem design that was under investigation. The algorithm made used this value and information from the database to adjust the cost estimate based on an average heritage level for each subsystem.

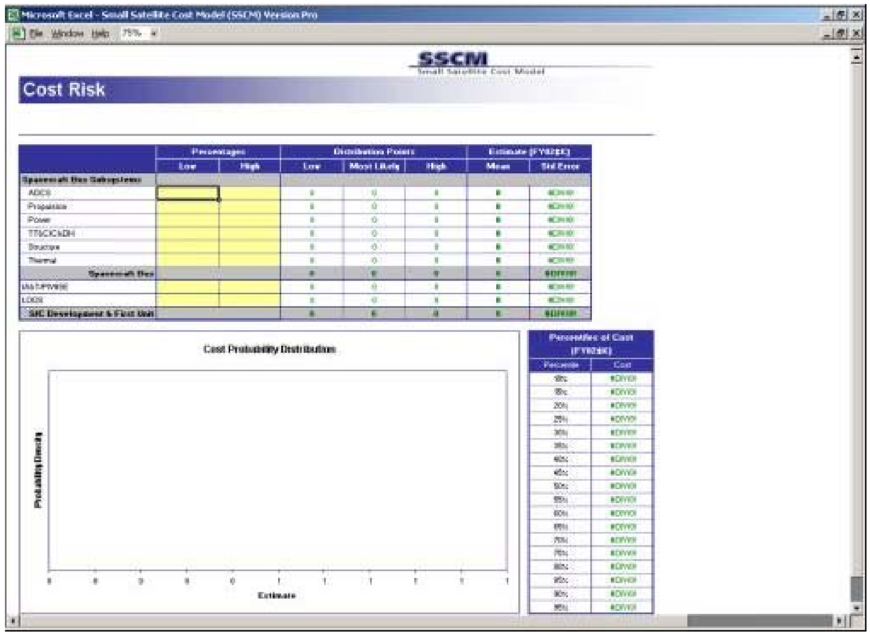

Figure 18-1 - SSCM Risk Input screen

Both of the uncertainty features in SSCM were based on assumptions about the state of the technology within the database on which the CERs are based. This database has grown since the last release of SSCM, casting doubt on whether these simplifying but necessary assumptions still hold true. Because of this uncertainty, the TRL-based and heritage-based risk adjustments have been removed from this version of SSCM and replaced with the simplified scheme discussed below. We continue to investigate the aspects of heritage and technology development that impact cost, and expect to reintroduce a revised cost-risk methodology in a future version of SSCM.

A simplified scheme for adjusting the cost estimate based on technical risk and heritage has been implemented for SSCM02, see Figure 18-1 for an image of the input screen. This new scheme uses a triangular cost probability distribution for each subsystem, where the most likely cost (see Figure 18-2) is the output of the CER, and the upper and lower limits are user-defined. The user must identify, by percentages, the lowest possible cost for the subsystem (e.g. 10% below the most likely estimate), as well as the highest possible cost (e.g. 150% greater than the most likely estimate). A subsystem with very low design maturity and no flight heritage must have a much larger upper bound than a subsystem that has very good heritage and is very mature. This scheme allows the user to modify the cost-risk parameters for each subsystem to properly take into account the cost uncertainty due to technology development and heritage.

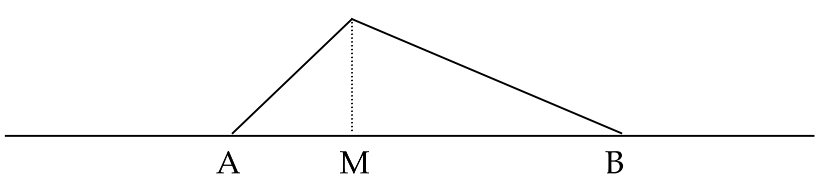

Figure 18-2 - Example of triangular distributions defined by the lower bound, *A*, upper bound, *B*, and the "most likely" estimate, *M*, derived from the CER. Depending on the user input, the triangle can have any shape, including a right triangle ($A = M$ or $M = B$), isosceles ($M - A = B - M$), or even a single point ($A = M = B$).

Two sources of risk for each cost element have been defined: general cost-estimating uncertainty and uncertainty due to design implementation. General cost-estimating uncertainty is quantified by SEE, while uncertainty due to design implementation is quantified by a triangular distribution defined by *A*, *B*, and *M*. These two sources of cost risk are merged into one cost-probability distribution that has a mean equal to the mean of the triangular distribution

$$Mean_{ss} = \frac{1}{3}(A + B + M) \tag{74}$$

and a variance that is equal to the sum of variances from both sources of uncertainty.

$$Var_{ss} = SEE^2 + \frac{1}{18}(A^2 + B^2 + M^2 - AB - AM - BM) \tag{75}$$

The system-level variance is also affected by the correlation of the errors in individual subsystems. Cross-correlation coefficients are needed to accurately capture the statistical effects of adding uncertainties [2, 3]. Correlation coefficients can be calculated in two ways: linear (Pearson's product-moment) correlation and rank (Spearman's) correlation [4]. In short, Pearson's product-moment correlation is a measure of the linearity between two random variables and Spearman's rank correlation is a measure of the monotonicity between two random variables. In SSCM, linear correlation coefficients are derived and used because the sum of random variables depends on the Pearson's product-moment correlation and not the Spearman rank correlation.

Correlation coefficients are generated for the relationship between each subsystem- and system-level element. The coefficients are calculated using

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - x_m)(y_i - y_m)}{\sqrt{\sum_{i=1}^{n}(x_i - x_m)\sum_{i=1}^{n}(y_i - y_m)}} \tag{76}$$

where r_{xy} is the correlation coefficient between two elements, *x* and *y* are errors from each element, and x_m and y_m are the average errors from each element. Correlation coefficients range in value range in value from –1 to +1. A coefficient of either –1 or +1 denotes that two subsystems are perfectly correlated; the error in one subsystem will be directly reflected in the subsystem that it is correlated to. The correlation coefficients for SSCM are given in Table 18-1.

Table 18-1 - Correlation coefficients for SSCM

	ADCS	Propulsion	Power	TT&C/ C&DH	Structure	Thermal	IA&T/ PM/SE	LOOS
ADCS	**1.00**	-0.41	-0.04	0.36	-0.34	0.33	-0.43	0.24
Propulsion		**1.00**	0.06	0.24	-0.14	-0.22	-0.61	-0.45
Power			**1.00**	-0.17	0.46	0.08	0.22	-0.03
TT&C/C&DH				**1.00**	0.32	-0.15	-0.24	0.31
Structure					**1.00**	0.20	0.57	0.50
Thermal						**1.00**	-0.03	0.40
IA&T/PM/SE							**1.00**	0.49
LOOS								**1.00**

The variance from the correlation coefficients is added to the variance for the CER and risk uncertainty for generate the variance for the total spacecraft and total system according to [5].

$$Var_t = \sum_{i=1}^{n} Var_{ss} + 2\sum_{k=2}^{n}\sum_{j=1}^{k-1} \rho_{jk}\sigma_j\sigma_k \qquad (77)$$

where ρ_{jk} is the correlation coefficient between elements *j* and *k*, and σ_j and σ_k are the standard deviations for elements *j* and *k* calculated from the original variance equation. The first term represents the sum of the element variances, while the second term is the covariance calculated from the correlation coefficients.

With the total system variance calculated, a cost-probability distribution can be generated. Research by The Aerospace Corporation and the MITRE Corporation has shown that this distribution may be accurately approximated by a lognormal distribution [6]. This approximation technique allows confidence percentiles to be computed without Monte Carlo simulation. The end product of cost-risk assessment in this framework is a total spacecraft cost-probability distribution, from which mean, standard deviation, percentiles, and other descriptive statistics can be read.

Estimation of Outside the Range of Validity

Parametric cost models have certain advantages and disadvantages, as do all cost estimation techniques. One of the disadvantages of such models is that the user is generally limited to applying the CERs to the database range, which we have termed the "range of validity". For example, if a subsystem's CER were based on that subsystem's mass, and the underlying database ranged from 5 kg to 50 kg, one would be hesitant (and rightly so) to apply the CER to a subsystem weighing 80 kg; as one strays further from the range of validity, one would expect the CER estimate to be less reliable. Applying CERs outside the range of validity makes two assumptions: (1) the CER remains valid beyond the data range; and (2) the SEE does not change outside the data range. The first assumption is not all that unreasonable, based on some studies done with data points outside the SSCM universe. For example, an in-depth analysis was made with SSCM version 1.0 CERs using the planetary spacecraft NEAR (Near Earth Asteroid Rendezvous), which went beyond the SSCM database range in several cases; the results were quite decent overall [7].

Furthermore, in the absence of additional information, there is little reason to doubt the CER trend in the near vicinity of the data range; that trend may be less certain as one goes further away from the range of validity. The second assumption, however, is questionable at best, and unreasonable at worst; there is greater uncertainty as one deviates further from the database range. The SEE is a statistical measure whose value is based on the underlying data; by the very nature of the problem, there is no way to analytically compute a new value outside the range of validity. Further, SEE is a measure of cost-estimating uncertainty, not CER-applicability uncertainty. The problem here is one of data-insufficiency; there is simply not enough data available to make an analytical estimate of the behavior of the variance outside the range of the database.

In the current version, the SEE is not adjusted outside of the range of validity of the input data. Previous versions of SSCM afforded the user the two ways to deal with data outside the range of validity. If the user felt that the CER applied to her input data, even though the data are outside of the range of validity, then either the SEE that is associated with that CER was accepted, or user manually increased the SEE to a level that she felt was appropriate. This implementation was selected only after several other methods were investigated, including penalizing SEE by an amount proportional to how far one exceeds the database range, and using subsets of the data, re-deriving CERs, and then applying the CER to points outside the subset to get an indication of the magnitude of error. Because of the wide range of possible scenarios, which may cause the cost driver to be out of range, none of these methods seemed acceptable. Thus, the user needs to take great care to examine cases where the input data is outside of the range of validity, and make a sound engineering judgment about whether the CER remains applicable. Aerospace is researching new, groundbreaking methods for estimating the SEE based on the spread of the input data, but they are not yet ready for implementation in this version of SSCM.

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19. Unmanned Space Vehicle Cost Model

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Introduction

The Unmanned Space Vehicle Cost Model, Eighth Edition (USCM8), is a parametric estimating tool based on cost estimating relationships (CER) built from a factual historical database [1]. Among other things, it provides CERs for estimating unmanned, earth-orbiting space vehicle costs. In addition it provides a work breakdown structure (WBS), a database description, Minimum Unbiased Percentage Error (MUPE) regression statistics for those CERs and an example calculation using USCM-8.

This section will demonstrate how to perform an example cost risk analysis using USCM-8. It will use the example provided with the model as a basis for this cost risk demonstration. The analysis is calculated using Crystal Ball®, a third party software NOT supplied with USCM-8. There are two facets to calculating risk in the model:

- Standard Error of the Estimate, whose values are in USCM-8
- Estimating error around the CER inputs. This information and calculation is done outside of the model

Space Vehicle Example of Cost Risk

An example space vehicle cost estimate using the USCM8 subsystem-level unique bus and payload CERs is provided in Table 19-1. It shows the input values used for each independent variable in our example. Following Table 19-1 we demonstrate how risk and uncertainty are applied to the CERs, their input variables and learning assumptions.

Table 19-1: Example Inputs

CER	Category	Cost Drivers	Input	Units
Integration, Assembly, & Test (IA&T)	Nonrecurring	Spacecraft Total Nonrecurring Cost	144,370	FY00$ (K)
	Recurring	Space Vehicle First Unit Cost	93,721	FY00$ (K)
Structure/Thermal	Nonrecurring	Beginning of Life Power	2,355	W
		Experimental Program (1=Yes, 0=No)	0	
	Recurring	Structure Weight + Thermal Weight	5,656	LB
		Number of Mechanisms	4	
Attitude Determination and Control System (ADCS)	Nonrecurring	ADCS Weight	615	LB
	Recurring	ADCS Weight	615	LB
Electrical Power Supply (EPS)	Nonrecurring	EPS Weight	1,223	LB
	Recurring	EPS Weight	1,223	LB
Telemetry, Tracking and Command (TT&C)	Recurring	TT&C Suite Weight	240	LB
		GEO Orbit (1=Yes, 0=No)	1	
Communications (Comm)	Nonrecurring	Communications Subsystem Weight	498	LB
		Number of Channels	17	
	Recurring	Communications Subsystem Weight	498	LB
Program Level SEPM (for Communication Satellites)	Nonrecurring	Space Vehicle Nonrecurring Cost	292,903	FY00$ (K)
	Recurring	Space Vehicle Recurring Cost	200,150	FY00$ (K)
Aerospace Ground Equipment	Nonrecurring	Spacecraft Total Nonrecurring Cost	144,370	FY00$ (K)
		Mission Type (1=Non-Comm Sats, 0=Comm Sats)	0	
Launch Operations & Orbital Support (LOOS)	Recurring	Average LOOS Cost	4,295	FY00$ (K)

Uncertainty in CERs

Each of the USCM8 CERs has an uncertainty, or percent standard error of the estimate ($SEE_{\%}$) associated with it. The $SEE_{\%}$ is the root-mean square of the percentage error residuals about the regression line, corrected for degrees of freedom and is calculated as:

$$SEE_{\%} = \sqrt{\frac{1}{n-p}\sum_{i=1}^{n}\left[\frac{y_i - f(x_i)}{f(x_i)}\right]^2} \qquad (78)$$

Where:

n = number of pairs of data points
p = number of parameters in CER.

The $SEE_{\%}$ is a good indicator of the percentage error of a CER, however true prediction error is based on correcting the $SEE_{\%}$ to account for the “distance” the estimating point lies from the center of the database relative to the range of the database. For the purposes of this example the $SEE_{\%}$ is used to measure the CER’s predictive capability. The $SEE_{\%}$ for the USCM8 NR and T1 CERs is provided in Table 19-2.

Table 19-2: Percent Standard Error for USCM8 Subsystem Level CERs

WBS Element	NR $SEE_{\%}$	T1 $SEE_{\%}$
Structure/Thermal	17	24
ADACS	44	36
EPS	41	31
TT&C	60	18
Propulsion	34	34
Total Bus		
Comm	40	39
IA&T	42	34
SEPM	23	12
AGE	37	
LOOS		65

We apply the $SEE_{\%}$ to the example cost estimate by multiplying all of the CERs by normal distributions that have a mean of 1.0 and a standard deviation equal to the $SEE_{\%}$ pertaining to that CER. As an example of this, we applied the $SEE_{\%}$ pertaining to the USCM8 Nonrecurring Structure and Thermal CER as shown in Equation 56. In this equation, the PDF is nominally equal to unity, which does not affect the output of the CER until it is defined as an assumption cell in **Crystal Ball** (Note this is a software application not provided with USCM). Figure 19-1 describes the parameters of the PDF as a Crystal Ball assumption cell.

$$STHNR = aX_1^b c^{X_2} \cdot pdf_{STHNR} \tag{79}$$

where:

a, b, and c are coefficients of the regression

X_1, X_2 are CER input variables, and

pdf_{STHNR} is the normal distribution representing the $SEE_{\%}$.

Assumption: STHNR

Normal distribution with parameters:

Mean	1.00	
Standard Dev.	0.17	(=O2)

Selected range is from -Infinity to +Infinity

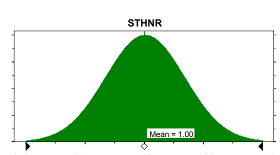

Figure 19-1 - Crystal Ball Assumption Cell Representing and Example CER Error

Risk and Uncertainty in Input Variables/Cost Drivers

In order to capture cost risk coming from the technical schedule and performance characteristics of the satellite under analysis, methods outside the USCM8 model must be employed. One method involves evaluating the CER input variables. The following is a brief description of this approach.

The risk and uncertainty in the CER input variables are applied to the model by defining random variables for the appropriate cost drivers. In our example, we defined a triangular PDF for each of the weight inputs for the USCM8 CERs shown in Table 19-3. The table shows the CER input variables along with an associated PDF and a nominal value for the CER input. Some of the USCM8 input variables are dummy variables that do not require modeling in cost risk analysis, so only the nominal, static values were used in this example.

Table 19-3: Uncertainties Applied to USCM8 Input Variables

WBS Element	X1	PDF	Value	X2	PDF	Value	X3	PDF	Value	X4	PDF	Value
Structure/Thermal	STRX1	1	2355	STRX2		0	STRX3		4	STRX4	1	5656
ADACS	ADACSX1	1	615									
EPS	EPSX1	1	1223									
TT&C	TTCX1	1	240			1						
Propulsion	PropX1	1	100	PropX2	1	200						
Total Bus												
Comm	CommX1	1	498			17						
IA&T			144,369			62,339						
SEPM			292,903			192,757						
AGE			144,369			1						
LOOS												

An example of the mechanism used to transform a nominal, static CER input variable into a PDF is shown in Equation 57, which represents the combined weight of the Structure and Thermal subsystems. In Equation 57, we introduce a "switch" that allows the analyst the choice of running the Monte Carlo risk analysis with or without uncertainty in the CER input variables. If the analyst chooses to perform a Monte Carlo analysis with uncertainty in the CER input variables, the switch is set to one, and the nominal weight of the Structure and Thermal subsystems is multiplied by the PDF representing its uncertainty. If the switch is set to any other number, the nominal static value of the weight is used, and the Monte Carlo simulation will ignore the effects of the uncertainty on the CER input variables.

$$\mathrm{STRX1} = 2355 * \mathrm{IF}(\mathrm{Tech\,Switch} = 1, \mathrm{PDFSTRX1}, 1) \tag{80}$$

Figure 19-2 describes the parameters of the PDF as a Crystal Ball assumption cell. In this example, as with all other weight input variables in the model, the PDF is based on the expected weight growth of the subsystem. The weight growth is modeled as a triangular distribution with a minimum of 1.0, a most likely value of 1.3 and a maximum value of 1.6.

Assumption: STRX1

Triangular distribution with parameters:

Minimum	1.00
Likeliest	1.30
Maximum	1.60

Selected range is from 1.00 to 1.60

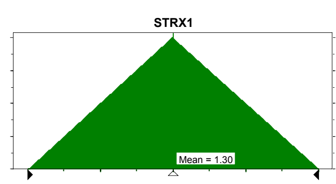

Figure 19-2 Crystal Ball Assumption Cell Representing an Example CER Input Variable Uncertainty

Correlation

As discussed previously in this handbook, correlation is an important factor in determining the variance and shape of the total cost risk distribution. In our example, two types of correlation exist: Functional correlation and statistical correlation. We will discuss each type of correlation and our method of handling them in the example model.

Functional Correlation

Functional correlation works simple like this: If a function, Y=f(X), is dependent on variable X, and X is a random variable, the output of the function is also a random variable that is transformed by the equation. There are several instances of inherent functional correlation in the USCM8 CERs. Many of the CERs are actual functions of the output of other CERs. For example:

- AGE Nonrecurring and the IA&T Nonrecurring and T1 costs are a function of the Total Bus Subsystem Nonrecurring and T1 costs
- SEPM Nonrecurring and T1 costs are a function of the Total Bus Subsystem + Communications Payload + IA&T Nonrecurring and Recurring costs respectively

In the USCM8 example we must first calculate the sum of the bus subsystem nonrecurring, T1 and recurring costs as shown in Figure 19-3. We then use the total bus nonrecurring and T1 costs to drive IA&T and AGE nonrecurring and T1 costs. Since the total bus nonrecurring and T1 costs are random variables in our Monte Carlo simulation, the *drivers* for the IA&T and AGE CERs will be random variables as well. This will functionally force the *output* of the IA&T and AGE CERs to be random variables. This process is similar to defining the input variables for the SEPM CER, whereby the analyst combines the IA&T and spacecraft bus costs to get total space vehicle costs and uses this value of total space vehicle cost to drive the SEPM CER. Finally, the analyst combines total space vehicle cost, SEPM, AGE and LOOS for total space vehicle estimate. All of this functional correlation defined by the selection of cost dependent drivers for CERs helps define the uncertainty in the total space vehicle cost distribution.

WBS Element	X1	pdf	Value	X2	pdf	Value	Total Nonrecurring	Total T1	Total Recurring
Structure/Thermal	STRX1	1	2355	STRX2		0	30,417	25,297	48,065
ADACS	ADACSX1	1	615				66,587	16,462	31,278
EPS	EPSX1	1	1223				27,603	13,222	25,122
TT&C	TTCX1	1	240			1	19,762	7,358	13,980
Propulsion	PropX1	1	100	PropX2	1	200	519	2,493	
Total Bus							144,369	62,339	118,444
Comm	CommX1	1	498			17	120,381	31,382	59,626
Total Spacecraft							264,751	93,721	178,070
IA&T			144,369			62,339	28,152.01	7,730.04	14,687
Total Space Vehicle							292,903	101,451	192,757
SEPM			292,903			192,757	69,125.04	45,105	
Total Space Vehicle							362,028	146,556	192,757
AGE			144,369			1	45,180.24		
LOOS								2,261.01	4,296
Total Estimate							407,208	148,817	197,053

Figure 19-3 Functional Dependencies of USCM8 CERs

Statistical Correlation

As mentioned earlier, there are two types of correlation in the USCM8 model: Functional correlation and statistical correlation. While functional correlation deals with the dependencies of CER inputs on the outputs of other CERs, statistical correlation between CER errors and other cost drivers (weight, in this example) also exists. The empirical, statistical correlation between the $SEE_{\%}$ of the USCM8 CERs was determined by Hu [2]. We modeled the correlation between the CER errors using the matrix shown in Figure 19-4 per these empirical correlations derived in the reference.

	STHT1	ADACST1	EPST1	TTCT1	COMMT1	IATT1	SEPMT1	STHNR	ADACSNR	EPSNR	TTCNR	COMMNR	IATNR	SEPMNR
STHT1	1.000	-0.300	-0.230	0.050	0.460	-0.070	0.440	-0.460	-0.430	0.000	0.000	0.820	-0.390	0.650
ADACST1		1.000	0.510	0.370	0.230	0.020	0.040	-0.680	0.030	0.550	0.000	-0.850	-0.420	0.000
EPST1			1.000	-0.080	-0.420	0.120	0.420	-0.550	0.250	0.640	0.000	0.000	-0.100	0.590
TTCT1				1.000	0.550	-0.010	-0.250	0.620	-0.710	0.060	0.000	-0.430	0.320	0.720
COMMT1					1.000	-0.280	-0.140	0.000	-0.170	-0.710	0.000	0.450	0.000	0.540
IATT1						1.000	0.470	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SEPMT1							1.000	-0.070	-0.350	0.450	0.000	-0.230	-0.430	-0.250
STHNR								1.000	0.010	0.000	0.000	-0.240	0.200	0.730
ADACSNR									1.000	0.350	0.000	-0.480	-0.400	-0.020
EPSNR										1.000	0.000	-0.640	0.330	0.130
TTCNR											1.000	-0.160	-0.520	-0.660
COMMNR												1.000	-0.040	-0.090
IATNR													1.000	0.000
SEPMNR														1.000

Figure 19-4 CER Error Correlation Coefficients

Another instance of statistical correlation exists between the cost drivers in the USCM8 model. The cost drivers in the example model used from USCM8 are subsystem weights for our example satellite. Our uncertainty in weight growth for subsystems is derived from the total spacecraft weight growth experienced on several programs, so to relate this weight growth to subsystems, we made the assumption that all subsystems will experience roughly the same weight growth. Because we used total spacecraft weight growth for an assumed subsystem weight growth, we essentially distributed the total weight growth among the subsystems. This assumption implicitly assumed perfect correlation (a value of 1.0) between all of the random weight variables. To correctly model this in statistical summation, they must now be correlated to a value of 1.0 in addition as shown in Figure 19-5.

	STRX1	ADACSX1	EPSX1	TTCX1	PropX1	PropX2	STRX4	CommX1
STRX1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ADACSX1		1.000	1.000	1.000	1.000	1.000	1.000	1.000
EPSX1			1.000	1.000	1.000	1.000	1.000	1.000
TTCX1				1.000	1.000	1.000	1.000	1.000
PropX1					1.000	1.000	1.000	1.000
PropX2						1.000	1.000	1.000
STRX4							1.000	1.000
CommX1								1.000

Figure 19-5 Cost Driver Correlation Coefficients

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Risk Bibliography

20. Risk Bibliography

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The following listing is a set of fundamental references, to the best of our knowledge, addressing cost estimating risk and uncertainty analysis. While not all-inclusive, this list represents a good subset of the most important references any cost risk analyst should be aware of. Please contact the editors if you notice any obvious omissions.

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